Necessity is the Mother of Invention: Input Supplies and Directed Technical Change*

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Abstract

The leading theory of directed technical change, developed by Acemoglu (2002), offers two main predictions. First, when inputs are sufficiently substitutable, a change in relative input supplies will generate technical change that augments inputs which become relatively more abundant. Second, if this effect is sufficiently strong, the relative price of the relatively more abundant inputs will increase – the strong induced-bias hypothesis. This paper provides the first empirical test of these predictions using the shock to the British cotton textile industry caused by the U.S. Civil War (1861-1865). Using detailed new patent data, I show that the shock increased innovation in Britain directed towards taking advantage of Indian cotton, which had became relatively more abundant. The relative price of Indian cotton first declined and then rebounded, consistent with strong induced-bias. Given my elasticity of substitution estimates, these findings are consistent with the predictions of the theory.
KEYWORDS: Directed Technical Change, Induced Innovation, Strong Induced Bias.

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1 Introduction

The idea that a change in the availability or price of inputs to production can play an important role in influencing the rate and direction of technical progress has been used to explain a diverse set of economic phenomena.[1] To cite one example, it has been suggested that the increase in skilled workers in the U.S. in the 1970s caused skill-biased *directed technical change*, and that this directed technical change allowed the skill premium to increase in spite of the increase in the relative abundance of skilled workers (Acemoglu (1998), Kiley (1999)). This example highlights two relationships which will be the focus of this paper. First, that a change in the relative supply of inputs can cause innovation to be directed towards technologies which augment either one or the other of the inputs. Second, that in some cases directed technical change can cause generate a positive long-run relationship between relative quantities of inputs to production and the relative price of those inputs.

These ideas have been formalized by by Acemoglu (2002, 2007), building on previous work by Hicks (1932) and others.[2] Acemoglu shows that the direction of technical change depends crucially on the elasticity of substitution between inputs, represented by σ. When this elasticity is low ($\sigma < 1$), technical change will be directed towards technologies that augment the input which has become relatively scarce. In contrast, when the elasticity of substitution between inputs is high ($\sigma > 1$), technical change will be directed towards technologies that augment the input which has become relatively more abundant. Next, he shows that, when the elasticity of substitution between inputs is sufficiently high ($\sigma > 2$), technical change will be so strongly directed towards technologies that augment the more abundant input that the relative price of that input can increase. This *strong induced-bias hypothesis* may explain, for

[1] In economic history, it has been suggested that a shortage of labor drove the development of labor-saving innovations which played an important role in industrialization in Britain and the U.S. (Habakkuk (1962), Allen (2009)). In the environmental literature, it has been pointed out that the impact of regulations that change the price of inputs, such as a carbon tax, will depend crucially on whether these changes generate directed technical change, and on the direction that this innovation takes (Acemoglu *et al.* (2012)). Related papers in the environmental literature include Porter (1991), Lanjouw & Mody (1996) and Jaffe & Palmer (1997). The idea of directed technical change has also been applied to consider the impact of high energy prices (Newell *et al.* (1999), Popp (2002)), the causes of cross-country productivity differences (Acemoglu & Zilibotti (2001), Caselli & Coleman (2006)), and agricultural productivity trends (Hayami & Ruttan (1970), Olmstead & Rhode (1993)).

[2] Other important contributions to this literature include Kennedy (1964), Samuelson (1965) and Drandakis & Phelps (1966).

example, how an increase in the supply of skilled workers may increase the skill wage premium.

The aim of this paper is to test these predictions. To do so, I consider a large exogenous shock to the British cotton textile industry caused by the U.S. Civil War (April 1861 - April 1865). The war, which included a blockade on Southern shipping by the Union Navy, sharply increased the cost of supplying U.S. cotton from the South, which provided most of the raw cotton imported into Britain prior to the war (77% in 1860). This forced British producers to turn to raw cotton from alternative suppliers, such as India, Brazil, and Egypt. In response to the resulting high prices, all of these alternative suppliers, led by India, substantially increased their exports to Britain. However, the cotton available from these alternative suppliers differed from American cotton in important ways. This was particularly true for cotton from India, the second largest supplier, which was a low-quality variety that was difficult to clean and prepare. This cleaning and preparation was undertaken using machines such as cotton gins, openers, scutchers, and carding machines. This fact that I can identify the specific types of machines needed for using Indian cotton allows me to identify the direction of technical change by tracking innovation patterns in these technologies relative to other types of cotton textile technologies. Thus, the Civil War generated a large exogenous shift in the relative supply of similar, but not identical, inputs to production that can be used to identify the causal impact on the direction of technical change and input prices.

This empirical setting has a number of features which are important for my study. First, the impact of the Civil War on the cotton textile industry was large and lasted for several years. There is evidence that output in the industry dropped by as much as 50%. Hundreds of thousands of mill operatives found themselves out of work or working short-time. Thus, this event was large enough to influence innovation rates. Second, I can compare outcomes in the the cotton textile industry to other similar textile industries – based on wool, linen, and silk – which were also important in Britain during this time, but which were not negatively impacted by the Civil War.[3] This will help me control for other time-varying factors that may be affecting innovation rates. Third, despite the magnitued of the shock, there was virtually no government intervention. This was primarily due to the strong free-market ideology

[3]If anything, these industries benefited somewhat from the reduction in competition from cotton textiles.

which was dominant in Britain at this time. This reduces the chance that the effects I observe are influenced by government action, which may be a serious concern in other contexts.

In order to identify the direction of technological change, I gathered new data on British patents containing a high level of detail on the types of new technologies being created. Using these patent data it is possible to track patterns of innovation in particular types of cotton textile machines. The patent data show that there was a substantial increase in cotton-textile related innovation during the Civil War period. This increase was concentrated in those machines that were particularly important for using Indian cotton. This increase peaked two to four years into the war, a time-frame that is consistent with qualitative evidence on the lag needed to produce new technologies such as cotton gins. The same features appear when I focus only on high-quality patents, using three measures of patent quality that I gathered. Thus, I find that the shock generated directed technical change towards the input which had become relatively more abundant, Indian cotton.

Next, using new data on the prices of these cotton varieties gathered from The Economist magazine, I look at the impact of the shock on relative input prices. In the absence of directed technical change, the price of alternative cotton varieties, relative to U.S. cotton, should have fallen as they became relatively more abundant. On the other hand, the technical change directed towards augmenting Indian cotton may offset this, by increasing the demand for that variety. Graphing the relative price of Indian to U.S. cotton shows a decrease in the first two years of the Civil War, followed by a rapid rebound starting in 1863, around the time when the new technologies were becoming available. This pattern is consistent with the strong-induced bias hypothesis. I contrast this with the pattern I observe for Brazilian cotton, a smaller alternative variety that does not appear to have benefited from directed technical change. I find that the relative price of Brazilian to U.S. cotton fell at the beginning of the war, as Brazilian cotton became relatively more abundant, and remained low throughout the period in which Brazilian cotton remained relatively abundant, consistent with what we would expect in the absence of directed technical change. Comparing these patterns econometrically allows me to control for other time-varying factors that affected the cotton industry. I show that there was a significant decrease in the relative price of Brazilian cotton over the ten years following the onset of the war. In contrast, the relative price of Indian cotton did not decrease and may have increased, on average, during this period, despite the large increase in the relative abundance of Indian cotton.

To relate these findings to the theory, I estimate the elasticity of substitution between Indian and U.S. cotton. Once I have this elasticity parameter, I know the predictions of the theory and can compare them to my empirical results in order to test the theory. I take two complementary approaches to estimating this parameter. First, I use an approach based on the Almost Ideal Demand System which has been widely used in the existing literature. However, I discuss some potential sources of bias that may be present in this approach. To address these, I use an alternative approach that exploits two other unexpected short-term shocks to the relative supply of Indian cotton. These are the Indian Mutiny of 1857, which disrupted economic activity and reduced exports of Indian cotton in 1858, and the Great Indian Famine of 1876-78, which directly impacted the cotton crop. Regardless of the approach used, I find evidence that the elasticity of substitution between Indian and U.S. cotton was above one and also likely above two. Given these, the model correctly predicts both the direction of technological progress and the impact of directed technical change on relative input prices.

Several previous empirical studies have also looked at the relationship between input supplies (or prices) and the direction of technological progress (Newell *et al.* (1999), Popp (2002), Aghion *et al.* (2010)).[4] The main feature that distinguishes this paper from these existing studies is that I observe the prices and quantities of multiple inputs into the production process. This means that I can estimate the elasticity of substitution between these inputs, derive the predictions of the theory, and compare these predictions to what I observe in the data. Also, previous studies used input prices as their main independent variable, which meant that they were unable to look at the impact of a change in relative quantities on relative input prices. Thus, this is the first study to investigate the strong-induced bias hypothesis. Another important

[4] An alternative approach is taken by Blum (2010) who uses cross-country trade data in an effort to find evidence of directed technical change at a macro level. In particular, he finds that changes in relative factor endowments are negatively correlated with relative factor prices, and that this correlation is larger for factor prices in the long run, which he interprets as evidence of technical change biased toward the factor which became relatively scarce. This approach is potentially complementary to microeconomic studies such as my paper. However, standing alone it is difficult to be sure that the changes he observes are truly due to directed technical change rather than other factors, since technology is not observed, and controlling for other potential explanations is difficult in a cross-country context.

difference is that this study uses a large exogenous shock to provide causal evidence in a cleaner way than was previously possible. A final difference is that my empirical setting is largely free of government intervention, which may be a concern in other settings.

While this study is focused on the impact of changes in input supplies on innovation, there are complementary studies that consider the influence of demand factors or competition. On the demand side, Acemoglu & Linn (2004) consider the impact of demand fluctuations on innovation rates in the pharmaceutical industry and find that shifts in demand can be an important driver of new product development. For competition, Bloom *et al.* (2009) use several measures of technical change, including patents and R&D expenditures, to show that an increase in competition from Chinese producers led European firms to upgrade their technology.

The next section presents the theoretical framework. Section 2 details the empirical setting and presents my elasticity estimates. The patent data are described in Section 4. I analyze the impact on innovation patterns using the patent data in Section 5. The impact on input prices is analyzed in Section 6. In Section 7 I estimate the elasticity of substitution parameters that determine the predictions of the theory and compare these predictions to my empirical results in order to evaluate the theory. Section 8 concludes.

2 Empirical setting

During the second half of the 19th century, cotton textiles were Britain's largest export and raw cotton was Britain's largest import.[5] For example, in 1860 cotton textile exports were valued at £52 million, dwarfing the next largest export categories, wool textile exports at £15.7 million and iron and steel at £13.6 million.[6]

2.1 The Cotton Textile Production Process

It is helpful to have some understanding of the cotton textile production process, and the technologies involved, before proceeding. There are four stages in the cotton tex-

[5] Of course, this was not the case during the U.S. Civil War.
[6] Data from Mitchell & Deane (1962).

tile production process: Preparation, Spinning, Weaving, and Finishing. Preparation involved separating the cotton fibers from the seeds, using gins, opening the cotton fibers using openers, and cleaning the cotton by removing leaves, dirt, and other matter using scutchers and carding machines.[7] In the spinning stage, the prepared raw cotton was spun into yarn.[8] The yarn was then made into fabric, through weaving, after which the fabric could be finished through bleaching, dying, or printing.

All of these production stages relied heavily on machinery which was supplied by Britain's large and innovative textile machinery sector. The two main textile technology categories, Spinning and Weaving, were among the top ten patent technology categories, out of 146 total categories, based on the number of patents filed from 1855-1883.[9] They made up 6% and 5%, respectively, of all British patents during this period, a time at which Britain was a world technology leader.

While cotton was the largest textile industry in Britain, textile industries based on wool, linen, and silk were also of significant size. The technology and other inputs used by these industries was generally similar to that used by the cotton textile industry.

2.2 The impact of the U.S. Civil War

The British cotton textile industry was entirely dependent on imported raw cotton, as growing cotton in Britain was infeasible. At the beginning of the study period, the cotton textile industry was heavily dependent on cotton growers in the U.S. South, as is evident in the left-hand panel of Figure 1. After the beginning of the U.S. Civil War in April of 1861 the North almost immediately declared a naval blockade of Southern ports. While initially ineffective, the blockade became increasingly disruptive to Southern commerce, including the export of raw cotton, as the war continued and the Union Navy expanded. While other suppliers, particularly India, but also Egypt and Brazil, attempted to increase output, they were not able to increase their production rapidly enough to replace the flows from the U.S. The right-hand panel of Figure 1

[7]Definitions of these and other textile-related terms are available in Appendix A.2. The first stage of the preparatory process, ginning, generally took place in the cotton producing region, while later stages, such as opening and carding, generally took place in manufacturing centers such as Britain.

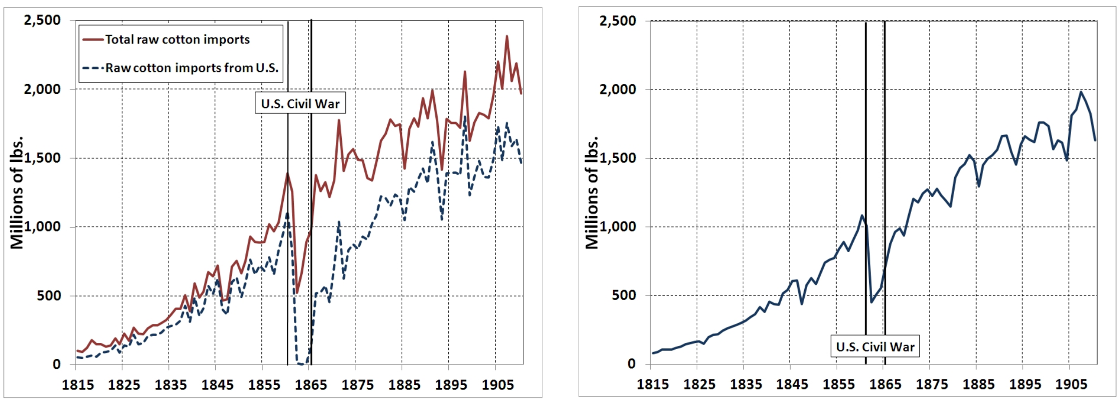
[8]This stage took place in Britain or other manufacturing centers.

[9]See Appendix A.1.

shows that there was a significant drop in British domestic cotton consumption from 1861-1865, a good indicator of production in the industry.[10]

Figure 1: British cotton imports and domestic consumption 1815-1910

British cotton imports British domestic cotton consumption



Data from Mitchell & Deane (1962).

Figure 2 shows the impact on the level of imports from each major supplier (left panel), and the share of total imports from the U.S., India, and other suppliers (right panel).[11] It is clear that the shock caused a sharp drop in imports from the U.S. and an increase in imports from other suppliers, particularly India. While imports from the U.S. dropped sharply during the war, significant supplies remained on the market, allowing me to obtain reliable price data for U.S. cotton throughout the shock period.[12]

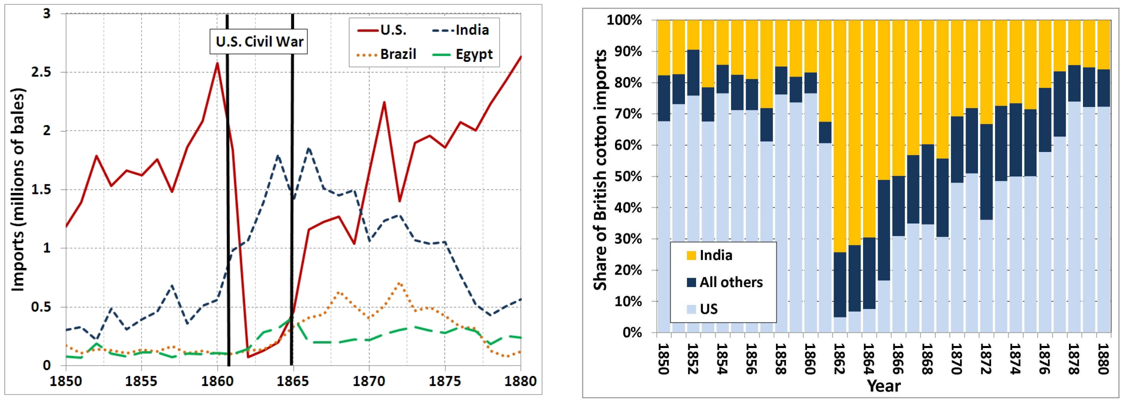
[10]It is reasonable to think of the amount of cotton required for a given amount of cotton textiles as being largely fixed, though, or course, small savings could be made. The reduction in production also led to massive unemployment in the cotton textile districts, resulting in the "Lancashire Cotton Famine". Brady (1963) argues that in fact the drop in production was driven by an oversupply of cotton textile goods on the market in 1860-1861, rather than a drop in the availability of inputs. His argument is based on the fact that the ratio of cotton stocks to imports remained high during the war. However, when one considers the size of the reduction in imports and the drawdown in stocks over the 1861-1865 period, rather than comparing ratios, it is clear that his argument cannot be correct.

[11]Note that the import data shown in Figure 1 and 2 come from two different sources. The Mitchell & Deane (1962) used in Figure 1 provide the longest time coverage but do not distinguish between imports from different sources.

[12]Imports from the U.S. never drop below 70,000 bales per year. For comparison, there were only 100,000 bales of Brazilian cotton imports in 1861.

Figure 2: British cotton imports and share of imports by supplier 1850-1880

Cotton imports by supplier 1850-1880 Share of imports by supplier 1850-1880



Data from Ellison (1886).

Two important points regarding the timing of the shock are visible in these figures. First, the war caused large changes during the 1861-1865 period. Second, following the end of the war, conditions began returning to their original equilibrium. The overall level of imports and production rebounded almost immediately, but the re-adjustment of relative input supplies took time. Imports of American cotton remained low through 1870, while imports of Indian, Brazilian, and Egyptian cotton remained high through the mid 1870's.

Another feature of this shock is that it was largely transmitted through the cotton textile industry, rather than being a broad-based economic shock. Once raw cotton imports are removed, total British imports do not appear to be affected during the shock period.[13] Similarly, once textile exports are excluded, British manufacturing exports also fail to show any large effect from the shock. Other main textile industries, based on wool, linen/flax, or silk inputs, showed no negative effects of the shock.[14] If anything, these sectors benefited from the reduced competition from cotton textiles.

[13]See Figure 16 in Appendix A.6.

[14]Graphs showing exports in these other sectors are available in Appendix A.6.

2.3 Differences between U.S. and Indian cotton

Understanding the differences between U.S. and Indian cotton is necessary in order to identify technologies which were needed specifically for using low-quality Indian cotton. The raw cotton supplied by the U.S. and India at the time of this study came from biologically distinct varieties. The cotton available from India in the 1860s was widely considered to be inferior to U.S. cotton in several important ways, a fact which was reflected in the lower price per pound paid for Indian cotton throughout the period I study (see Figure 7 in Section 6).

One difference between these varieties was that Indian cotton was more difficult to prepare for spinning. In particular, it was difficult to remove the seeds from the Indian cotton using the cotton gins which were available. This was a result of the unusually small size of the Indian cotton seeds, as well as their strong bond to the cotton plant (see, e.g., Wheeler (1862)). The primary machine used to remove seeds in India was the Churka, a very simple and inexpensive but inefficient and often ineffective hand-operated machine. The main alternative, prior to 1860, was the saw gin, which had been developed for processing American cotton.[15] However, American saw gins tended to cut up the Indian cotton fibers, reducing their length, and therefore their usefulness.[16] In addition, the saw gins were much more complicated and expensive. For these reasons the saw gin proved ill suited for India. In addition to the difficulty in removing seeds, Indian cotton fibers were also more difficult to open, a process which was done using openers.

The U.S. also had a better developed cotton growing and processing industry than India, which influenced the cleanliness of the cotton. Indian cotton had a difficult journey from the interior to the ports, and passed through the hands of multiple middle-men, who habitually added dirt, salt water, or other substances in order to increase the weight of the cotton.[17] As a result, the Indian cotton required more cleaning than American cotton, a process that was done using gins, scutchers, and carding machines.

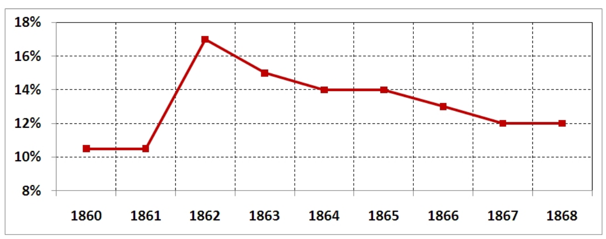
Indian and U.S. cotton also differed in their fiber length. Most of the raw cotton coming from the U.S. was of a medium-length-fiber variety, which was easier to spin

[15]Illustrations of both machines are available in Appendix A.3.
[16]See example in Appendix A.5.
[17]See, e.g., the description in Wheeler (1862) (p. 125-129) and Mackay (1853).

than the short-fiber cotton supplied by India.[18] The fact that Indian cotton was shorter likely compounded the difficulties involved in ginning, since using a gin could significantly shorten the fiber length.[19]

The difficulty that British producers faced in using Indian cotton is reflected in the share of cotton wasted in the production process, plotted in Figure 3. This graph shows that there was a sharp increase in cotton waste corresponding to the switch to Indian cotton in 1862. This is particularly striking given that price of raw cotton was very high by 1862, which must have induced producers to take measures to limit such waste. The slow reduction in the waste level after 1862 may indicate improvements in the ability of textile manufacturers to use Indian cotton efficiently.

Figure 3: Share of waste in total raw cotton input 1860-1868



Data from Forwood (1870). These values are calculated by taking the weight of cotton consumed and subtracting the weight of yarn produced, to obtain the weight wasted in the production process.

Another indicator of the differences between U.S. and Indian cotton can be found in the patent descriptions themselves. Though most patents provide only a simple description of the mechanisms involved, a few also mention the motivation behind the new technology. One example is Patent No. 2162 from 1862, which describes a patent filed in Britain in 1862 which was specifically designed to open the more tightly-compressed East Indian cotton.[20]

Qualitative evidence from historians and contemporary observers suggests that the differences between Indian and U.S. cotton was an influential factor during the

[18]Appendix A.4 shows a comparison of fiber lengths from several of the varieties of cotton available to British producers. The Indian varieties are shorter than all other varieties.

[19]This is illustrated in Appendix A.5, which shows the difference between the length of fiber obtained after hand-cleaning and mechanically ginning using a sample of Brazilian cotton.

[20]This patent was classified in the spinning technology category and the "Openers & Scutchers, etc." subcategory, and also has "cotton" in the patent title, leading it to be identified as a cotton-related patent. A description of this patent is available in Appendix A.8.

1861-1865 period. For example, the historian D.A. Farnie, in his authoritative history of the British cotton textile industry in the 19th century, emphasized the technological changes that using Indian cotton required British producers to undertake.[21] Contemporary observers, such as Ellison (1886) also remarked on the improvements in the quality and usefulness of Indian cotton that took place during this period.[22]

2.4 How long to invent new technologies?

Because this studies relies on the timing of the Civil War for identification, it is important to consider the lag that we should expect between an increase in the incentives for innovation and the production of patentable new technology designs. It is very difficult to address this concern rigorously, since the lag is likely to vary across technology types and individual inventors and the moment at which an inventor begins work on a problem is generally unobserved. However, historical evidence can provide some guide.

One piece of evidence that is particularly relevant for this study is provided by Lakwete (2003) in her authoritative history, *Inventing the Cotton Gin*. This account details numerous instances in which inventors produced new innovations or patentable improvements on existing inventions within a 1-3 year period. Among these inventors is Eli Whitney, who had invented, patented, and introduced commercially, his famous cotton gin, within two years of first setting foot on a Southern cotton plantation. Two other good examples are McCarthy's roller gin and Whipple's cylinder gin, which were both invented in response to the panic of 1837 and patented in the U.S. in 1840. These examples suggest that, at least in the case of gins, it is reasonable to expect innovation to respond to changing conditions within a two to three year time-frame.

[21] Farnie (1979) (p. 152-153) writes, "The shortage of American cotton compelled employers to re-equip their mills in order to spin Surat [Indian cotton], and especially to improve their preparatory processes...The process of opening the tightly packed raw material become wholly automated through the use of the Crighton Opener, invented in 1861, as was the subsequent process of scutching through the application of the ingenious piano-feed regulator developed in 1862...The reorganization of the preparatory processes entailed such an extensive investment of capital that it amounted almost to the creation of a new industry...Those innovations gave a great stimulus to the textile engineering industry and consolidated the technical supremacy of the Lancashire cotton industry in the world."

[22] In his book, *The Cotton Trade in Great Britain*, Ellison writes, "The high prices caused by the cotton famine, however, gave an impetus to the culture [of cotton] in India which it would not otherwise have obtained, and thereby secured to Europe a permanent increase in supply. Moreover, the quality of the cotton has been so materially improved by the introduction of better methods of handling the crop, that "Surats" are no longer despised as they were up to within a few years ago."

3 Theory

This section adapts the theory of Acemoglu (2002) to the empirical setting that I investigate. The main challenge in doing so is that the cotton textile industry uses multiple types of raw cotton inputs and the elasticity of substitution may vary across different input pairs. In order to accommodate this feature, I divide the cotton textile industry into high and low quality market segments and focus on the four main types of raw cotton inputs: Indian cotton, Brazilian cotton, lower-quality U.S. cotton, and higher-quality U.S. cotton. I index these input types, respectively, by $i \in \{I, B, USL, USH\}$. Products in the high-quality market segment are produced using higher-quality U.S. cotton or Brazilian cotton, while low-quality products are produced using lower-quality U.S. cotton or Indian cotton. Thus, within each market segment there are two inputs and the model is identical to that presented in Acemoglu (2002). However, the elasticities of substitution between inputs can vary across the different market segments, and there is also some substitutability in demand between low and high quality products.

3.1 Model setup

The model can be thought of as representing a small textile sector which is embedded in a larger economy, i.e., it is a partial equilibrium model. It is also dynamic, with continuous time. The textile sector produces low-quality and high-quality goods and consumption is over an index Y of these goods which takes a CES form,

$$Y = \left[Y_L^{\frac{\epsilon-1}{\epsilon}} + Y_H^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}},$$

where Y_L is an index over low-quality textiles, Y_H is an index of high-quality textiles, and $\epsilon \in (0, +\infty)$ is the elasticity of substitution between them. The corresponding price index P takes the standard form, where the price indices over low and high-quality goods are, respectively, P_L and P_H. The price index P is the numeraire. The Y_L and Y_H indices are given by,

$$Y_L = \left[y_I^{\frac{\rho_l-1}{\rho_l}} + y_{USL}^{\frac{\rho_l-1}{\rho_l}} \right]^{\frac{\rho_l}{\rho_l-1}} \quad \text{and} \quad Y_H = \left[y_B^{\frac{\rho_h-1}{\rho_h}} + y_{USH}^{\frac{\rho_h-1}{\rho_h}} \right]^{\frac{\rho_h}{\rho_h-1}},$$

where y_I is the quantity of goods produced using Indian cotton, y_B is the quantity of goods produced using Brazilian cotton, and y_{USL} and y_{USH} are the quantities of goods produced using lower and higher-quality U.S. cotton, respectively. The elasticity of substitution between products made with Indian cotton and those made with lower-quality U.S. cotton is $\rho_l \in (0, +\infty)$, while the elasticity of substitution between products made with Brazilian and higher-quality U.S. cotton is $\rho_h \in (0, +\infty)$. The corresponding price indices are,

$$P_L = \left[p_I^{1-\rho_l} + p_{USL}^{1-\rho_l}\right]^{\frac{1}{1-\rho_l}}, \quad \text{and} \quad P_H = \left[p_B^{1-\rho_h} + p_{USH}^{1-\rho_h}\right]^{\frac{1}{1-\rho_h}}.$$

The production function for each of these goods is,

$$y_i = \left(\frac{1}{1-\beta}\right)\left(\int_0^{N_i} x_i(k)^{1-\beta} dk\right) Z_i^{\beta}, \tag{1}$$

where N_i is the number of machine types available for producing good i, $x_i(k)$ is the quantity of each machine of type k specialized for the production of good i, Z_i is the input used to produce good i, and $\beta \in (0, 1)$. Inputs correspond to the varieties of raw cotton in the empirical setting, and each input is specific to the good it produces. The price of input i paid by input users, denoted c_i, corresponds to the price of raw cotton variety i on the British market.

Note that the level of technology related to each input type is represented by N_i and that these technologies are different for each i. This includes an assumption that different technologies are used for lower-quality U.S. cotton and higher-quality U.S. cotton.[23]

3.2 Short-run equilibrium (with technology fixed)

For each input type $i \in \{I, B, USL, USH\}$, textiles are produced by perfectly competitive firms which take output prices, input prices, and machine prices as given. It is straightforward to solve the final goods firms' optimization problem in order to

[23] We may be concerned that, in practice, many technologies which are developed for one input type can also be used for others. This is less of a concern because all of the main results generated by the model are in terms of relative technology levels (N_i/N_j). Thus, even if a technology can be used with both input i and input j, if it is relatively more useful for input i then it will result in an increase in N_i/N_j, i.e., directed technical change towards input i.

obtain expressions for the demand for machines and inputs. The resulting first-order conditions are,

$$x_i(k) = \left(\frac{p_i}{\chi_i(k)}\right)^{1/\beta} Z_i, \tag{2}$$

$$c_i = \left(\frac{1}{1-\beta}\right) p_i \left(\int_0^{N_i} x_i(k)^{1-\beta} dk\right) Z_i^{\beta-1}, \tag{3}$$

where $\chi_i(k)$ is the price for a unit of machines of type k used for producing good i.

New machines are produced by technology monopolists who face a constant marginal cost ψ. The profit for a monopolist producing a machine type k used for good i is $\pi_i(k) = (\chi_i(k) - \psi)x_i(k)$. Because the demand curve for machines is isoelastic, the optimal price charged by these monopolists is $\chi_i(k) = \psi/(1-\beta)$, and to simplify things, I apply the normalization $\psi = (1-\beta)$, which implies that equilibrium machine prices are $\chi_i(k) = 1$ for all i and k.[24] It is now possible to use the machine price and machine demand expressions to rewrite production as a function of only the goods price, the level of technology and the input quantity:

$$y_i = \left(\frac{1}{1-\beta}\right) p_i^{\frac{1-\beta}{\beta}} N_i Z_i. \tag{4}$$

One implication of having perfectly competitive final-goods producing firms and a constant elasticity of substitution between goods in each market segment is that we can obtain expressions for the relationship between relative prices and relative outputs within each segment. For example, within the low-quality textile segment I have,

$$\frac{p_I}{p_{USL}} = \left(\frac{y_I}{y_{USL}}\right)^{-\frac{1}{\rho_l}}. \tag{5}$$

Using Equations 2-5 I obtain the following expression for the relationship between relative input prices, relative technology, and relative input quantities within the low-quality textile segment:

[24] Note that, because machine producers are small, the pricing and production decisions of individual producers will not affect Z_i, so machine producers will not consider the impact of their collective pricing choices on the quantity of input i.

$$\frac{c_I}{c_{USL}} = \left(\frac{N_I}{N_{USL}}\right)^{\frac{\sigma_l - 1}{\sigma_l}} \left(\frac{Z_I}{Z_{USL}}\right)^{-\frac{1}{\sigma_l}}. \tag{6}$$

In this equation, $\sigma_l = 1-\beta+\beta\rho_l$ is the derived elasticity of substitution between inputs in the low-quality textile market segment. A similar expression can be obtained for the high-quality market segment, where the elasticity of substitution between high-quality inputs is $\sigma_h = 1 - \beta + \beta\rho_h$. This useful equation describes the short-run relationship between relative input supplies and relative prices.

Short-run result 1: Holding technologies fixed, an increase in the relative input quantities within a market segment (Z_i/Z_j) will have a negative impact on the relative input prices within that segment (c_i/c_j).

Next, begin considering the long-run setting in which technology varies endogenously. I begin by looking at the incentives for producing new machine designs and the costs of these innovations.

3.3 Incentives and costs of innovation

Given that machine prices equal one, and using the machine demands from the final-goods producer's first-order condition, instantaneous profits for a technology monopolist firm making machines for industry i are, $\pi_i = \beta\ p_i^{1/\beta}\ Z_i$. Machines depreciate fully after use, but machine designs remain available indefinitely. Thus, technology monopolists care about their discounted value of future profits, rather than instantaneous profits, when deciding whether to develop new machines. The net present discounted value can be written using a standard dynamic programming equation as, $rV_i - \dot{V}_i = \pi_i$, where r is the interest rate, V is the present discounted value of future profits, and π is the flow of profits. Focusing on the steady state, where $\dot{V} = 0$ and the interest rate is constant, the discounted value of developing a machine of type i is,

$$V_i = \frac{\beta p_i^{1/\beta} Z_i}{r}. \tag{7}$$

This expression reveals the two key forces that determine the impact of an increase in Z_i on innovation. An increase in Z_i in Equation 7 has a direct positive influence on the incentives for innovating in technologies that augment input i. Acemoglu calls this the *market size effect*. However, an increase in Z_i will also increase output y_i which will reduce the price p_i. Thus, an increase in Z_i will act to reduce the incentives for innovation in technologies that augment input i through this indirect *price effect*. The relative strength of these two effects will depend on how strongly p_i depends is affected by an increase in Z_i, which depends on the elasticity of substitution between final goods, or equivalently, on the derived elasticity of substitution between inputs.

Using Equation 7, I obtain the relative value of producing each machine type within the low and high quality segments. For example, within the low-quality market segment I obtain,

$$\frac{V_I}{V_{USL}} = \left(\frac{N_I}{N_{USL}}\right)^{-\frac{1}{\sigma_l}} \left(\frac{Z_I}{Z_{USL}}\right)^{\frac{\sigma_l - 1}{\sigma_l}}. \tag{8}$$

This equation shows that, when the elasticity of substitution between factors is high ($\sigma_l > 1$), an increase in the quantity of input i will increase the incentive for new inventions that augment input i. The opposite will occur when $\sigma_l < 1$. Similar results hold in the high-quality market segment.

I now turn to the cost of innovation which is modeled in a very simple way. The production of a new machine design costs a fixed amount η of final output according to the function $\dot{N}_i = \eta R_i$ where R_i represents expenditure on innovation in these machines. For simplicity, I assume that η does not vary across different machine types, though allowing for this does not affect the main predictions of the theory.

3.4 Long-run results (with technology varying)

I focus on the balanced growth path in which each technology type progresses at the same rate. Within each market segment, balanced growth implies that $\dot{N}_i = \dot{N}_j$ for all i and j. It follows that $\dot{V}_i = 0$ and $V_i = V_j$. Using this together with 8, I can show that in the low-quality market segment it must be the case that,

$$\frac{N_I}{N_{USL}} = \left(\frac{Z_I}{Z_{USL}}\right)^{\sigma_l - 1}. \tag{9}$$

This equation delivers the first long-run result generated by the theory.

Long-run result 1: Directed technical change. Within a market segment, an increase in the relative quantity of one input induces an increase in the relative technology that augments that input when the elasticity of substitution between the inputs is greater than one. When the elasticity of substitution is less than one, an increase the relative quantity of one input leads to a reduction in the relative level of the technology that augments that input.

Next, derive the long-run relationship between relative quantities and relative prices. Using Equations 9 and 6, I obtain,

$$\frac{c_I}{c_{USL}} = \left(\frac{Z_I}{Z_{USL}}\right)^{\sigma_l - 2}. \tag{10}$$

The second main long-run result of the theory is clearly visible in this equation.

Long-run result 2: Strong induced bias. Within a market segment, an increase in the relative quantity of one input induces an increase in the relative price of that technology when the elasticity of substitution between the inputs is greater than two. When the elasticity of substitution is less than two, and increase in the relative quantity of one input leads to a reduction in the relative price of that input.

These two results are familiar from Acemoglu (2002). Thus, within a market segment the theory reproduces the key results of Acemoglu's theory. In addition, we can also look at how changes in input availability affects relative technology levels across the two market segments. To start, perfect competition in final goods implies that,

$$\frac{P_L}{P_H} = \left(\frac{Y_L}{Y_H}\right)^{-\frac{1}{\epsilon}}. \tag{11}$$

On the balanced growth path with diversified technologies, I must have $V_i/V_j = 1$ for any $i, j \in \{I, B, USL, USH\}$. Using this, together with the results generated above, it is possible to derive the following expression (details available in the Appendix):

$$\frac{Z_I}{Z_B} = \left(\frac{N_I}{N_B}\right)^{\frac{1}{\beta(\epsilon-1)}} \frac{\left[1 + N_{USL}/N_I\right]^{\frac{\sigma_l - 1 + \beta(1-\epsilon)}{\beta(1-\sigma_l)(1-\epsilon)}}}{\left[1 + N_{USH}/N_B\right]^{\frac{\sigma_h - 1 + \beta(1-\epsilon)}{\beta(1-\sigma_h)(1-\epsilon)}}}. \tag{12}$$

This equation describes the relationship between input quantities and technology levels across market segments, delivering the following result.

Long-run result 3: DTC across market segments. Holding the relative input quantities in each market segment (Z_I/Z_{USL} and Z_B/Z_{USH}) constant, so that relative technology levels within each segment remain constant, an increase in Z_I/Z_B will increase N_I/N_B when $\epsilon > 1$.

4 Data

4.1 Patent data

The primary data used to measure innovation in this study come from British patent records. While imperfect, patent data is the best available quantifiable measure of technological advance during this period. Modern patent data has been widely used in recent studies of innovation, building on seminal work by Schmookler (1966), Scherer (1982), Griliches (1984), and Jaffe *et al.* (1993). Hall *et al.* (2001) provide a helpful review of the advantages of using patent data, including that (1) patents contain highly detailed information, (2) there are a large number of patents available to study, and (3) patents are provided on a voluntary basis under a clearly defined set of incentives. This study is able to take advantage of thousands of patents and will draw heavily on the detailed information available in the patent descriptions. While British patent laws changed in 1852 and 1883, they were stable during the period of this study.

One disadvantage of using patent data is that it will not capture all types of innovation. Evidence from Moser (2010) shows that a significant fraction of new inventions went unpatented during the period I study. However, her results also suggest that, among all categories, inventions of manufacturing machinery – the primary focus of this study – were the most likely to be patented. The incentive to patent appears to have been particularly strong for textile machinery, which was relatively easy to reverse-engineer.[25] Thus, this concern appears to be less important in the context studied here. A second concern is that patent counts may not reflect the underlying quality of the new inventions, which can vary widely. This concern is addressed using several measures of patent quality.

[25] See Moser (2010).

Much of the data used in this study was collected for the purpose of this project from around 1,500 pages of printed British patent records. To begin, I constructed a database covering all of the patents granted in Britain between 1855 and 1883, 118,863 in all.[26] The novel contribution of this data set is that each patent is classified into one or more of 146 technology categories by the British Patent Office (BPO). These classifications allow me to identify the type of technology underlying each patent. The purpose of this categorization was to aid inventors in identifying previously patented technologies in order to determine whether an invention was in fact new. My focus will primarily be on two BPO categories which I will call "Preparation & Spinning" and "Weaving & Finishing".[27] The Preparatory & Spinning category includes technologies related to the preparation of raw cotton, such as cotton gins and carding machines, machines used in the spinning process, such as mules, yarn types, and other related technologies. The Weaving & Finishing category includes technologies such as looms, types of fabrics, and fabric treatments.

These data are supplemented with information from the *A Cradle of Invention* database, which has been used in previous research (e.g., Brunt *et al.* (2008)).[28] This database provides the titles of the patents, which are not available in the patent data I collected. Patent titles can be used to generate more detailed classifications of the technology represented by each patent. In particular, I undertake keyword searches of these titles to identify patents related to the main textile inputs: cotton, wool, linen/flax, and silk.[29] Consistent patent titles are available from 1853-1870, after which there was a clear structural change in the naming conventions, with much less detail included in the patent titles available in the data.[30] This database also provides information on the month of the patent application, allowing analysis at the sub-annual level.

[26]These data include both granted patents and those which received provisional protection but where a patent was not ultimately granted.

[27]The British Patent Office calls these categories Spinning and Weaving, but I use these names to make it clear that the preparatory machines are included in the spinning technology category.

[28]I thank Tom Nicholas for suggesting this data source. These data are available through MFIS LTD (finpubs.demon.co.uk). These data match the primary database reasonably well, with over 98% of patents in the two databases matching, though this database is slightly less comprehensive than the one I collected.

[29]More details are available in Appendix A.9. This technique has been used previously with these data by Brunt *et al.* (2008).

[30]The average number of characters in the patent titles is over 70 for the years before 1871. This drops to just under 28 characters on average starting in 1871.

Conveniently, the dates given in the data represent the date of the patent application, rather than the date at which the patent was ultimately granted.[31] Thus, the application dates allow me to identify patents at the earliest stage of the patenting process.

Within each BPO technology category, patents may also be listed in various technology subcategories. For example, within the BPO Preparatory & Spinning technology category, it is possible to identify patents falling into subcategories such as “Gins”, “Mules and Twiners”, “Carding Machines”, etc. Data were gathered on patents fitting into several of the larger technology subcategories, which are described in in Table 1.[32] These can be divided into those related to the preparatory, spinning, or finishing stages of the spinning process. The data are available from 1855-1876. Of the subcategories shown, the most important for adapting to the use of Indian cotton were gins, openers/scutchers, and to a lesser extent, carding machines.[33]

Table 1: Preparatory & Spinning technology subcategories by production stage

Preparatory stage	**Patents**	**Spinning stage**	**Patents**	**Finishing stage**	**Patents**
Gins	122	Mules and twiners	446	Finishing	332
Openers/scutchers	331	Rollers for spinning	462		
Carding	696	Bearings for spinning	242		
Combing	354				

Patent counts for BPO Preparatory & Spinning technology subcategories, 1855-1876.

[31]In the British system at this time, patent applications cost £25, considered a substantial sum at the time, and could be made using only basic information on the invention. A sum of £25 in 1860 was equal to £1,840 2009 pounds, when deflating by the retail price index, or £16,300, when deflating by average earnings (calculator available at from the Measuring Worth project at www.measuringworth.com). The application provided the applicant with provisional protection and could aid them in establishing the seniority of their invention. The applicant was then responsible for supplying full patent specifications within six months or the patent became void. Patents lasted for 14 years but renewal fees had to be paid at years three and seven in order to keep the patent in force. For more information on the British patenting system during this period see Van Dulken (1999).

[32]Note that “finishing stages of the spinning process” denotes operations occurring as part of the spinning stage of production, such as bleaching or dyeing yarn, as opposed to the finishing stage of the textile production process as a whole, which involved bleaching, dyeing, etc. of woven fabrics. Thus, it falls into the Preparatory & Spinning category rather than the Weaving & Finishing category.

[33]See Section 2.

4.2 Patent quality measures

Adjusting for quality is important when using patent data because raw patent counts mask the quality of the new technology represented by each individual patent, which may vary widely.[34] I take advantage of three measures of patent quality in order to evaluate whether the 1861-1865 period was also characterized by an increase in the number of high-quality cotton-textile-related patents. The first measure is based on the payment of patent renewal fees. These were expensive fees that British patent holders were required to pay at the end of the third and seventh years of the patent term in order to keep the patent in force.[35] Since just under 18% of patents were renewed at three years the payment of these renewal fees represents a substantial investment which would only have been worth it for the most successful technologies.[36] The second quality measure is the based on whether technologies patented in Britain were also filed in India.[37] Patents of innovations which proved to be particularly useful are presumably more likely to be patented in multiple locations. The third quality measure is based on mentions of the patent in a contemporary periodical, *Newton's London Journal*.[38] This monthly journal, devoted to covering new patents and other technology-related topics, was published by William Newton & Sons, one of the preeminent London patent agents. While similar, each of these three measures captures a distinct aspect of patent quality.[39] Most of these quality measures are based on new data sets collected for this purpose. A detailed description of the data are available in Appendix A.11.

[34]Of particular concern is the possibility that a number of patents may represent inventions of limited usefulness. This is unlikely to be the case given the relatively high patent fees charged in Britain at this time (Khan (2005)), but it is still important to adjust for patent quality.

[35]Renewal fee data have been used as an indicator of patent quality in previous studies (Schankerman & Pakes (1986), Lanjouw *et al.* (1998)), including some using historical British patent data (Sullivan (1994), Brunt *et al.* (2008)).

[36]Because so few observations of patents renewed at year seven are available, the following results use only the renewals filed at year three.

[37]This approach has been used previously by Lanjouw *et al.* (1998).

[38]A similar approach has previously been used to value historical British patents by Nuvolari & Tartari (2011).

[39]While these aspects of quality are likely to be correlated, it is also possible to think of situations in which they may differ, which is why multiple measures of patent quality are considered.

4.3 Price and quantity data

To evaluate the strong induced-bias hypothesis, new price data was gathered from market reports printed in *The Economist* magazine. The data cover 1852-1880 and were gathered from original sources. While the data were collected on a monthly basis, I aggregate the data to quarters to reduce short-term volatility and measurement error. The Economist price data are available for the following benchmark cotton varieties: Upland Middling from the U.S., Upland Ordinary from the U.S., Surat Fair from India, Pernambuco Fair from Brazil, and Egyptian Fair. Of the two U.S. varieties, the Upland Middling was a higher quality variety that was more comparable to the high quality cotton from Brazil and Egypt, while the Upland Ordinary was a lower quality variety that was more comparable to Indian cotton. Thus, in relating the data to the theory, Upland Ordinary will represent lower-quality U.S. cotton and Upland Middling will represent higher-quality U.S. cotton. When longer series are needed I will supplement these data with less detailed annual data from Mann (1860) covering 1820-1859 and Ellison (1886) covering 1820-1884.

To estimate the elasticity of substitution between inputs I will also need data on the quantity of cotton imported by Britain from each of these suppliers. For this purpose I primarily use annual data from Ellison (1886) which is available from 1820-1884. Additional data is also available from Mann (1860) annually for 1820-1859. One drawback of both of these datasets is that they aggregate all U.S. cotton together, so it is not possible to identify separately imports of higher and lower-quality varieties. In Section 7 I discuss the potential bias that this feature introduces.

5 Directed technical change

This section explores the impact of the Civil War shock on innovation patterns. I proceed in two steps. First, I look at patent data on the broad technology categories related to textile production in order to establish that there was a significant increase in textile-related innovation in response to the shock. Further, I show that this increase was concentrated in technologies related to cotton textiles and that no similar increase occurred for technologies related to wool, linen, or silk textiles. These results show that the shock generated a significant response by textile innovators, and that this response was concentrated in cotton textile technologies. However, they do not reveal shifts in the direction of technological progress.

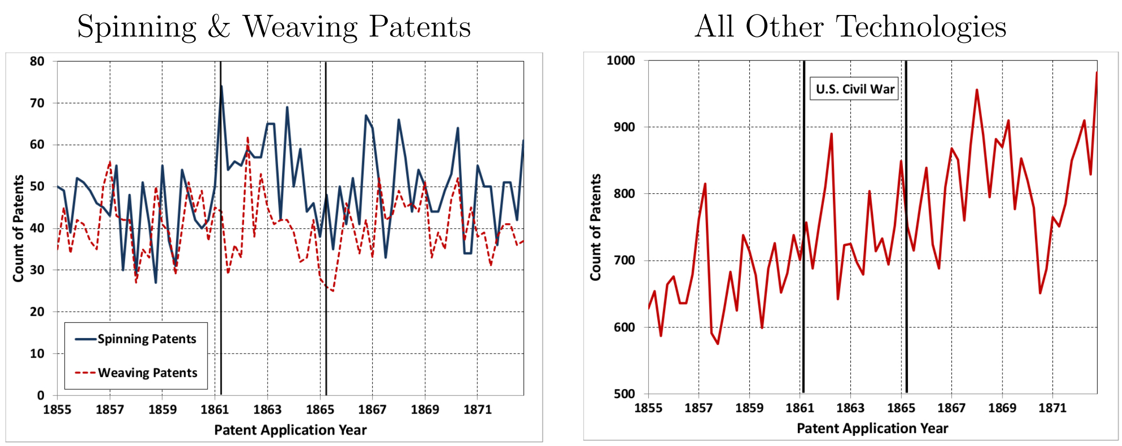
Second, I use data on patents related to specific types of textile machinery in order to assess the influence of the shock on the *direction* of technological progress. Three types of textile machinery – gins, openers/scutcher, and carding machines – were particularly important for using Indian cotton. A shift in innovation towards these machine types can thought of as an increase in N_I relative to other technology types. Thus, these results reveal the impact of the change in relative input supplies (Z_I/Z_{USL}) on relative technology levels (N_I/N_{USL}). Together with the elasticity of substitution estimates generated in Section 7, these results can be used to evaluate the theoretical prediction shown in Equation 9. This is the first main result of the paper, so I explore both the timing and robustness of the observed effects.

5.1 Overall impact of the shock on textile technologies

I begin by looking at patenting patterns in the 146 technology categories identified by the British Patent Office. Two of these, spinning and weaving, include the technologies used by the textile industry. The spinning category includes all technologies used in the early stage of the production process, including those technologies specifically related to the use of Indian cotton. The weaving category contains technologies used in the later stages of the production process. These broad categories include, in addition to technologies related to cotton textiles, those related to wool, linen, silk, and other textile industries.

Our first glimpse of the patent data is presented in Figure 4. The left-hand panel graphs patent counts for the BPO spinning and weaving technology categories. The right-hand panel shows similar data for all BPO technology categories except spinning and weaving. Even in the broad spinning technology category it is clear that the shock to cotton textiles generated a response by innovators. Two main patters are visible in these graphs. First, patenting of spinning technologies shot up in the second quarter of 1861, corresponding with the start of the war. Second, there was a sustained high level of patenting of spinning technologies throughout most of the Civil War period, with patents only dropping as the war wound down in 1865. My focus will be on the second of these features, which I will argue represented the introduction of previously unknown technologies to the cotton textile production process. In contrast, the initial spike in patents was almost certainly due to the patenting of existing (but not yet widely implemented) ideas which suddenly became valuable as a result of the onset of the war. No similar increases appear for weaving technologies, nor do non-textile technology categories display any sustained high level of patents similar to that shown by the spinning technology category.

Figure 4: Patent counts from BPO technology categories

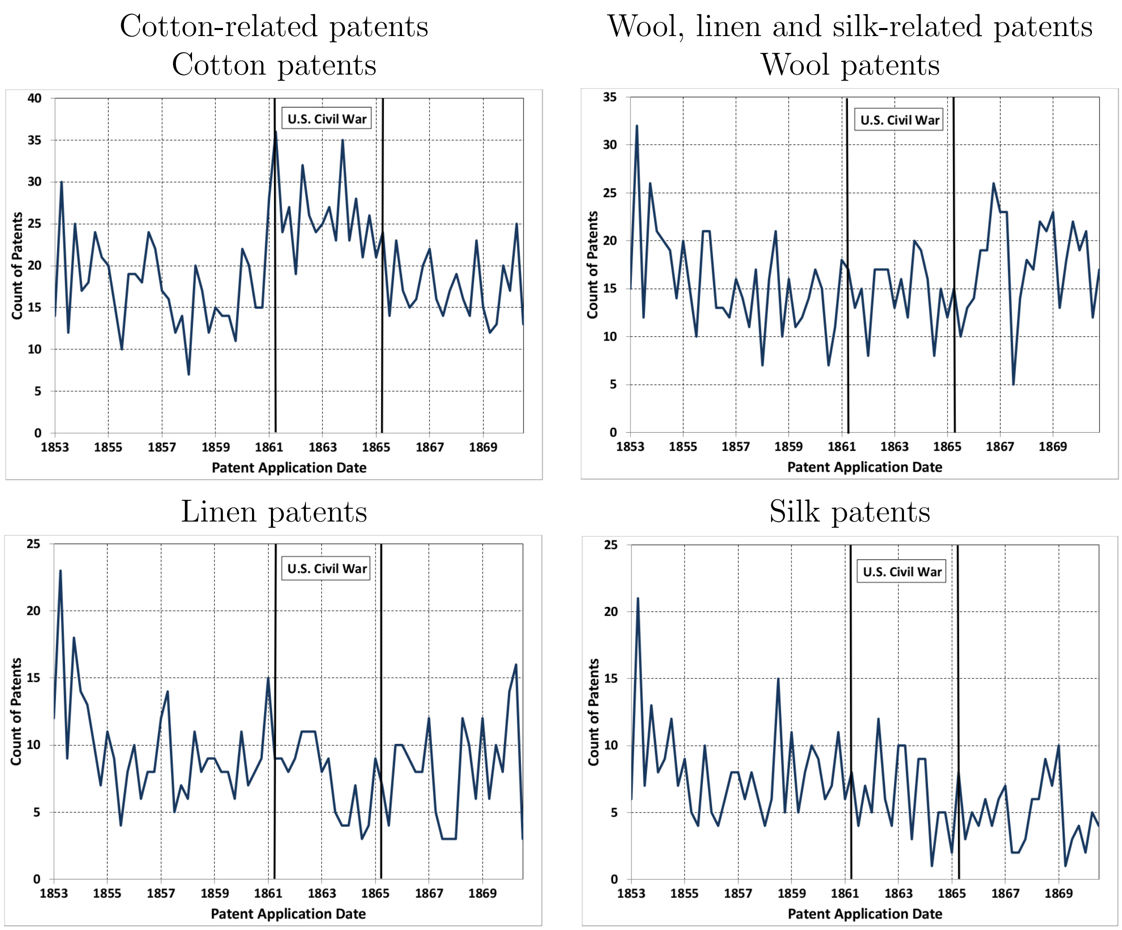


Next, I look within the spinning technology category at whether these new patents were related to cotton textiles. I do so by comparing the pattern of cotton textile patents to those related to the three other major textile industries in Britain at this time, wool, linen, and silk. This is done in Figure 5.

We can see that there was a substantial increase in cotton textile technology patents at the onset of the war. More importantly, there was a sustained high level of cotton textile technology patents throughout the Civil War period, with the level dropping only in early 1865 as the war wound down.

These patterns can be established econometrically, though, because these results are not as important as those to come I merely outline them here and confine the details and full regression results to Appendix A.10. First, using a panel data regression approach I show that there was a statistically significant increase in the level of cotton textile patents during the shock period, relative to wool, linen, and silk-related patents. Then, using wool, linen, and silk to control for time-varying factors, I focus on the timing of the impact on the cotton textile industry. I find that the increase in cotton textile patents started in 1861 and persisted through 1865, with the peak level occurring in 1864 in all specifications. These results establish that the Civil War caused a significant increase in innovation in cotton textile technologies. Next, I investigate the direction of this innovation.

Figure 5: Count of patents with titles mentioning main textile inputs, 1853-1870



5.2 Impact on the direction of technological progress

To investigate the direction of the technical change that occurred during the Civil War, I use the data on patents in technology subcategories within the BPO Preparatory & Spinning technology category, shown in Table 1. Two of these subcategories, gins, and openers/scutchers (and to a lesser extent, carding machines) can be directly linked to the use of Indian cotton because they address the main technological bottlenecks in the use of that variety. Thus, changes in the relative importance of these categories can be used to identify a shift of innovation activity towards or away from technologies which augment Indian cotton. In terms of the model, an relative increase in innovation in the technologies most closely related to Indian cotton can be interpreted as an increase in N_I/N_{USL}.

I begin the analysis by graphing the count of patents, by year, for each technology subcategory, in Figure 6. These graphs show an increase in patents in technology subcategories related to the preparation of raw cotton, particularly gins and openers/scutchers, during the 1861-1865 period. In contrast, technologies related to later stages of the spinning process do not show similar effects. It is particularly interesting that there does not appear to be an increase in combing machine patents. These machines were not used in producing every type of yarn, but when they were used they were the largest source of cotton waste.[40] The next most wasteful stage was carding, which shows only modest evidence of an increase. If innovation had been focused primarily on economizing on waste cotton, I would expect to see an increase in patents of combing and carding technologies. The fact that we do not suggests that innovation was not directed towards economizing on cotton in general.

Next, I analyze these patterns using a regression approach. First, I want to test whether the gins and openers/scutchers subcategories are exhibiting different behavior during the shock period relative to the other technology subcategories within the set of textile technologies. To do this, I pool data from all of the subcategories, which I index by $j \in J$, and consider,

$$P_{jt} = f\left(\sum_{j=1 \in J} \gamma_i \times S_t \times I_j + \phi_j + \xi_t + TT_{jt} + e_{jt}\right), \tag{13}$$

where P_{jt} is the count of patents in subcategory j, S_t is an indicator variable for the shock period (1861-1865), I_j is an indicator variable for subcategory j, ϕ_j is a full set

[40]See Thornley (1912). Combing machines act somewhat like a standard comb. Their purpose was to remove short fibers and arrange the remaining longer fibers so that they are all pointing the same direction. Combing was generally done when producing higher quality fabrics. While combing machines were used to produce cotton, they were more common in the preparation of wool (worsted) textiles.

of subcategory fixed effects, TT_{jt} is a subcategory-specific time-trend, ξ_t is a full set of year indicator variables, and e_{jt} is an error term. I use the general function $f()$ here because I will be taking two regression approaches. First, I will calculate standard linear panel-data regressions using Feasible Generalized Least Squares (FGLS) where I allow for heteroskedasticity within panels, correlation across panels, and AR1 serial correlation within panels with panel-specific serial correlation parameters. Second, I may be concerned about the presence of zeros in the data, even though these are not common in the main subcategory data.[41] In order to deal with any potential bias that these may create, I will calculate additional results using Negative Binomial regressions.[42]

Regression results based on Equation 13 are shown in Table 2. Columns 1-3 contain results generated using a linear FGLS model, while columns 4-6 contain results generated using Negative Binomial regressions. All regressions include subcategory fixed effects. In addition, columns (2) and (5) include year indicator variables and columns (3) and (5) add in subcategory-specific time-trends.

Table 2 shows that the shock period was characterized by a significant increase in patents in gins. There is also evidence of an increase in patents in the openers/scutchers subcategory, though this increase is not statistically significant in all specifications. None of the other categories show consistent evidence of an increase during the Civil War years. Thus, it appears that the increase in innovation generated by the Civil War was heavily concentrated in the two categories most important for the use of Indian cotton.

[41] Four out of 176 subcategory-year bins include zero patents.

[42] Negative Binomial regressions are preferred to Poisson regressions because most of the data series are characterized by overdispersion.

Figure 6: Patent counts in subcategories of the BPO Spinning technology category

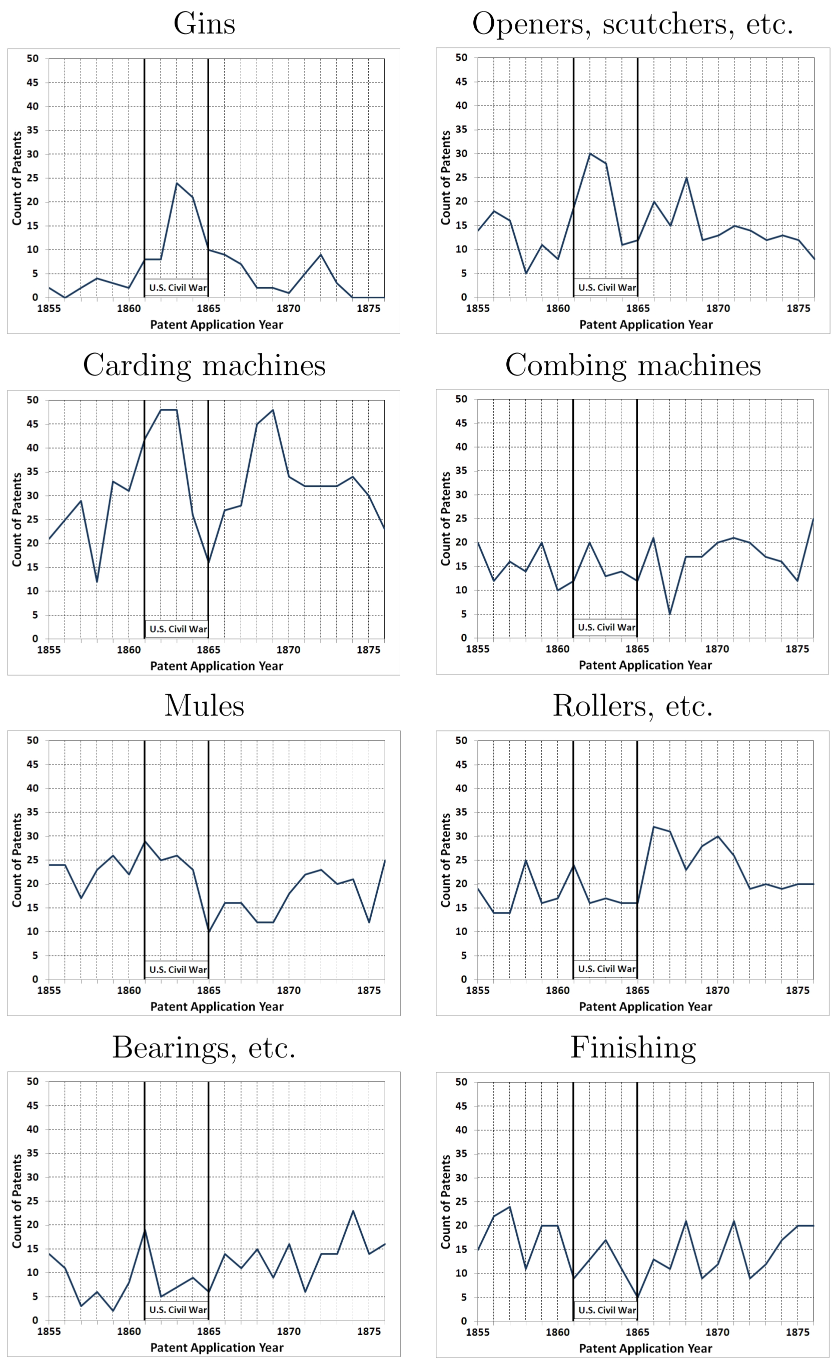


Table 2: Panel regressions across textile technology subcategories

	DV: Number of patents					
	FGLS regressions			**Negative Binomial regressions**		
	(1)	(2)	(3)	(4)	(5)	(6)
Bearings x Shock period	-6.255**	-6.136**	1.046	-0.530**	-0.729***	-0.203
	(2.991)	(2.850)	(2.434)	(0.252)	(0.264)	(0.263)
Carding x Shock period	3.368	1.466	5.152	0.0658	-0.123	0.375**
	(5.877)	(5.622)	(4.794)	(0.158)	(0.179)	(0.187)
Combing x Shock period	-0.690	-1.477	3.950	-0.0830	-0.278	0.182
	(1.868)	(2.208)	(2.477)	(0.192)	(0.209)	(0.214)
Finishing x Shock period	-2.949	-4.210	0.508	-0.323	-0.515**	-0.0977
	(2.390)	(3.358)	(3.086)	(0.215)	(0.228)	(0.233)
Gins x Shock period	13.77***	13.57***	18.23***	1.550***	1.364***	1.773***
	(1.817)	(2.123)	(2.370)	(0.198)	(0.219)	(0.240)
Mules x Shock period	0.795	0.00802	5.578*	0.0385	-0.153	0.257
	(3.225)	(3.163)	(3.073)	(0.175)	(0.193)	(0.203)
Openers x Shock period	7.434**	5.870*	10.35***	0.344**	0.158	0.606***
	(3.224)	(3.119)	(2.359)	(0.172)	(0.192)	(0.204)
Rollers x Shock period	-8.953***	-6.417**	-0.0829	-0.265	-0.463**	-0.0185
	(2.906)	(2.992)	(3.168)	(0.192)	(0.207)	(0.209)
Subcategory TT (p value)			[0.000]			[0.000]
Year effects	No	Yes	Yes	No	Yes	Yes
Observations	176	176	176	176	176	176
Number of subcategories	8	8	8	8	8	8

Regressions run on annual panel data from 1855-1876. All regressions include subcategory-specific fixed effects. Standard errors are shown in parenthesis. In the FGLS specifications, standard errors are robust to heteroskedasticity, correlation across panels, and AR1 serial correlation with panel-specific serial correlation parameters. All regressions include subcategory fixed effects.

Next, I want to explore the timing of these impacts by focusing on the gins and openers/scutchers technologies. I use the following specification,

$$\log(P_{jt}) = f\left[\sum_{k=1858}^{1868}\left(\gamma_k^G \times Y_k \times GINS + \gamma_k^O \times \xi_k \times OPENERS\right) + \phi_j + \xi_t + TT_{jt} + Q_t + \epsilon_{jt}\right]$$

where $GINS$ and $OPENERS$ are indicator variables for the gins and openers/scutchers subcategories, respectively. The results are shown in Table 3 which presents linear regression results generated using FGLS in columns (1)-(3) and additional Negative Binomial regression results in columns (4)-(6). These results consistently show that patents of gins increased at the start of the Civil War in 1861, reached the highest level 2-3 years into the war (1863-1864), and then tapered off towards the end of the war. The openers/scutchers category shows consistent evidence of an unusually high level of patents in 1862-1863.

The results shown in Tables 2 and 3 suggest that the Civil War period was characterized by an increase in innovation in those technologies related to Indian cotton. This is the main result of the paper related to directed technical change. The remainder of this section investigates the strength of these observed effects in more detail.

By combining the data on the various textile industry with the data on the technology subcategories, it is possible to verify that the increase in gins and openers/scutcher innovations was concentrated in the cotton textile industry. To do this, I use negative binomial regressions according to,

$$\log(P_{ijt}) = f\left(\sum_{i=1}^{I}\sum_{j=1\in J}\gamma_{ij}\times S_t\times I_j\times J_j+\phi_j+\theta_i+\xi_t+e_{ijt}\right),$$

where as before i indexes industries (cotton, wool, linen, and silk), j indexes technology subcategories, S_t is an indicator variable for the shock period (1861-1865), I_i is an indicator variable for industry i, and J_j is an indicator variable for technology j. The model includes a full set of industry fixed effects ϕ_i, subcategory fixed effects θ_j and year effects ξ_t.

Table 4 presents the results, which are generated from a single regression but are displayed by industry and subcategory. It is clear from this graph that the increase in gin patents was concentrated in the cotton textile industry and in fact gin technologies were simply not used in the Linen and Silk industries. For openers/scutchers, I observe negative coefficients for all of the industries other than cotton. Note that the results for openers were weaker than those for gins, so it is not surprising that with this very fine cut of the data the cotton x openers coefficient is not statistically significant, though it remains positive.

Table 3: Timing of effects on gins and openers/scutchers technologies

	FGLS regressions			**Negative Binomial regressions**		
	(1)	(2)	(3)	(4)	(5)	(6)
Gins x 1858	1.819	5.911***	4.478**	0.637	0.894	0.974
	(1.551)	(2.155)	(2.182)	(0.558)	(0.565)	(0.642)
Gins x 1859	-0.243	-0.0358	-1.918	0.353	0.371	0.435
	(1.726)	(2.216)	(2.250)	(0.630)	(0.633)	(0.689)
Gins x 1860	0.276	2.392	0.982	-0.0452	0.0358	0.0939
	(1.772)	(2.223)	(2.235)	(0.752)	(0.755)	(0.792)
Gins x 1861	6.753***	3.918*	2.636	1.324***	1.201***	1.247***
	(1.787)	(2.224)	(2.211)	(0.424)	(0.431)	(0.483)
Gins x 1862	4.649***	4.427**	2.889	1.324***	1.285***	1.315***
	(1.792)	(2.225)	(2.190)	(0.424)	(0.433)	(0.470)
Gins x 1863	21.21***	20.70***	19.59***	2.419***	2.369***	2.395***
	(1.794)	(2.224)	(2.171)	(0.301)	(0.317)	(0.354)
Gins x 1864	18.60***	23.27***	22.44***	2.286***	2.455***	2.486***
	(1.792)	(2.223)	(2.156)	(0.312)	(0.330)	(0.353)
Gins x 1865	7.271***	17.14***	16.36***	1.546***	2.132***	2.149***
	(1.787)	(2.221)	(2.144)	(0.392)	(0.414)	(0.420)
Gins x 1866	6.663***	5.685**	4.936**	1.441***	1.391***	1.397***
	(1.772)	(2.214)	(2.133)	(0.406)	(0.415)	(0.416)
Gins x 1867	5.740***	7.802***	7.569***	1.192***	1.356***	1.343***
	(1.725)	(2.194)	(2.123)	(0.446)	(0.456)	(0.452)
Gins x 1868	1.474	-1.426	-1.784	-0.0452	-0.165	-0.186
	(1.550)	(2.111)	(1.966)	(0.752)	(0.753)	(0.747)
Openers x 1858	-10.18***	-6.205***	-6.837***	-0.910*	-0.672	-0.885*
	(1.442)	(2.043)	(1.543)	(0.539)	(0.520)	(0.517)
Openers x 1859	-3.994**	-3.660	-6.471***	-0.150	-0.137	-0.332
	(1.738)	(2.323)	(1.496)	(0.381)	(0.371)	(0.372)
Openers x 1860	-7.044***	-5.261**	-6.911***	-0.460	-0.384	-0.555
	(1.862)	(2.416)	(1.513)	(0.439)	(0.424)	(0.419)
Openers x 1861	4.406**	3.150	1.209	0.386	0.258	0.102
	(1.920)	(2.453)	(1.494)	(0.300)	(0.297)	(0.296)
Openers x 1862	15.75***	16.57***	13.62***	0.837***	0.796***	0.655***
	(1.945)	(2.467)	(1.486)	(0.248)	(0.255)	(0.253)
Openers x 1863	13.58***	13.23***	11.44***	0.769***	0.715***	0.597**
	(1.953)	(2.471)	(1.475)	(0.255)	(0.261)	(0.256)
Openers x 1864	-3.225*	1.799	1.022	-0.150	0.00822	-0.0785
	(1.945)	(2.466)	(1.468)	(0.381)	(0.373)	(0.362)
Openers x 1865	-1.655	8.608***	6.740***	-0.0654	0.512	0.442
	(1.919)	(2.448)	(1.461)	(0.367)	(0.371)	(0.357)
Openers x 1866	7.384***	6.916***	4.877***	0.436	0.382	0.331
	(1.862)	(2.404)	(1.456)	(0.294)	(0.293)	(0.281)
Openers x 1867	1.818	3.670	2.899**	0.153	0.312	0.271
	(1.737)	(2.293)	(1.439)	(0.333)	(0.331)	(0.318)
Openers x 1868	12.02***	9.364***	8.817***	0.657**	0.543**	0.528**
	(1.441)	(1.982)	(1.326)	(0.268)	(0.269)	(0.258)
Subcategory TT (p value)			[0.000]			[0.006]
Subcategory FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	No	Yes	Yes	No	Yes	Yes
Observations	176	176	176	176	176	176
Number of subcategories	8	8	8	8	8	8

Regressions run on annual panel data from 1855-1876. Standard errors are shown in parenthesis. In the FGLS specifications, standard errors are robust to heteroskedasticity, correlation across panels, and AR1 serial correlation with panel-specific serial correlation parameters. All regressions include subcategory fixed effects. The indicator variable for the first year is omitted.

Table 4: Subcategory x industry x shock period coefficient estimates

	Bearings	Carding	Combing	Finishing	Gins	Mules	Openers	Rollers
Cotton	-0.564	0.00453	-1.668***	-0.512	1.686***	0.254	0.360	-0.475
	(0.414)	(0.304)	(0.422)	(0.446)	(0.326)	(0.334)	(0.314)	(0.338)
Wool	-0.731	-0.341	0.157	-0.479	-1.242	-0.628	-0.588	-0.693*
	(0.500)	(0.339)	(0.320)	(0.506)	(0.770)	(0.455)	(0.404)	(0.388)
Linen	-0.829	-0.807	-0.334	-0.171	NA	-1.014	-0.973	-0.134
	(0.766)	(0.497)	(0.439)	(0.653)		(0.766)	(0.646)	(0.439)
Silk	-1.515	NA	-0.0388	1.222***	NA	-1.700	-0.119	-1.225*
	(1.043)		(0.407)	(0.420)		(1.042)	(0.477)	(0.645)

Coefficient estimates are all from a single Negative Binomial regression run on panel data with two cross sectional dimensions (industries and subcategories). Regression run on annual data from 1855-1876. The shock period is defines as 1861-1865. Regression includes a full set of industry fixed effects, subcategory fixed effects, and year indicator variables. Negative Binomial regressions are warranted because the data are sparse, with 263 out of 704 subcategory x industry x year bins having zero patents.

When using patent data, it is always important to account for the quality of inventions, which will be obscured when only raw patent counts are used. Using a Negative Binomial version of the specification described in Equation 13, I generate results for two of the patent quality measures discussed in section 4. Negative Binomial results are preferred here because these data are more sparse and therefor contain more zero observations. Table 5 summarizes the results. Full regression results and additional details are available in the Appendix. All of these quality measures suggest a statistically significant increase in patent applications of high-quality patents of cotton gins filed during the Civil War period. In contrast, none of the other categories show consistent evidence of an increase or decrease during the same period.

In addition, there is evidence that this period saw an increase in patents of cotton textile related technologies, and gins in particular, in India. Using the Indian patent data, I run some simple regressions to look at whether there was an increase in the share of these technologies in Indian patents, relative to all other technology types, during the Civil War period. Because I do not observe patents related to other textile industries or to technology subcategories other than Gins, these results, presented in Table 6, are based on simple time-series regressions with Newey-West standard errors to help control for serial correlation.

Table 5: Coefficient estimates for high-quality patents in textile subcategories

	Patents with renewal fees paid at year three	Patents with abstracts in *Newton's London Journal*
Bearings x Shock period	-2.649***	0.369
	(1.026)	(0.577)
Carding x Shock period	-0.445*	0.410
	(0.246)	(0.418)
Combing x Shock period	0.0804	0.543
	(0.287)	(0.640)
Finishing x Shock period	-0.741**	-0.401
	(0.362)	(0.567)
Gins x Shock period	1.640***	1.978***
	(0.470)	(0.715)
Mules x Shock period	-0.0398	0.592
	(0.283)	(0.511)
Openers x Shock period	-0.141	0.628
	(0.313)	(0.566)
Rollers x Shock period	-0.368	0.561
	(0.329)	(0.531)
Subcategory FEs	Yes	Yes
Year effects	Yes	Yes
Observations	112	80
Number of panels	8	8

Column 1 contains results from a Negative Binomial regression run on annual data from 1856-1869. Column 2 contains results from a Negative Binomial regression run on annual data from 1855-1864. All regressions include a full set of subcategory fixed effects and year indicator variables.

Table 6: Cotton textile technology patents in India during the Civil War

	Share of all Indian patents		**Share of patents by British inventors**	
	Cotton	Gins	Cotton	Gins
Shock Indicator	0.0442**	0.0249**	0.126**	0.0720**
(1861-1865)	(0.0173)	(0.0103)	(0.0515)	(0.0319)
Observations	23	23	23	23

Table contains results from time-series regressions using annual data from 1856-1879. Standard errors are Newey-West with a lag length of 2. This approach assumes heteroskedastic standard errors while allowing for serial correlation up to a lag length of two.

Together, the results presented in this section suggest that there was an substantial increase in cotton textile patents during the Civil War period and that this increase was driven by patents of cotton gins, a technology which was particularly important for the use of Indian cotton. Patenting of gins reached its peak two to four years into the war. Moreover, patents of high-quality gin technologies also increased during the war. Thus the Civil War was characterized by directed technical change focused on technologies which augmented Indian cotton.

6 Strong-induced bias

This section explores the impact of a change in relative input supplies on relative input prices in the presence of directed technical change. My main focus will be on the relative price of Indian to lower quality U.S. cotton. I consider four hypothesis.

Hypothesis 1: The increase in the relative supply of Indian to U.S. cotton caused by the Civil War reduced the relative price of Indian cotton in the short run.

This hypothesis corresponds to the main short-run prediction of the theory. I will test this hypothesis by looking at the time path of the relative price of Indian cotton during the first two years of the war. The remaining three results are long-run results motivated by the evidence of directed technical change towards Indian cotton described in the previous section.

Hypothesis 2: Directed technical change towards Indian cotton had a positive effect on the relative price of Indian cotton.

This is a relatively weak hypothesis derived from Equation 6 in the model with N_I/N_{USL} allowed to vary. It can be tested by comparing the relative price of Indian cotton to that of Brazilian cotton or other varieties for which I did not find evidence of directed technical change. A stronger hypothesis is:

Hypothesis 3: Directed technical change toward Indian cotton offset the effect of the increase in relative supply such that the relative price of Indian cotton did not decrease even though it became relatively more abundant.

Finally, we have the strongest hypothesis:

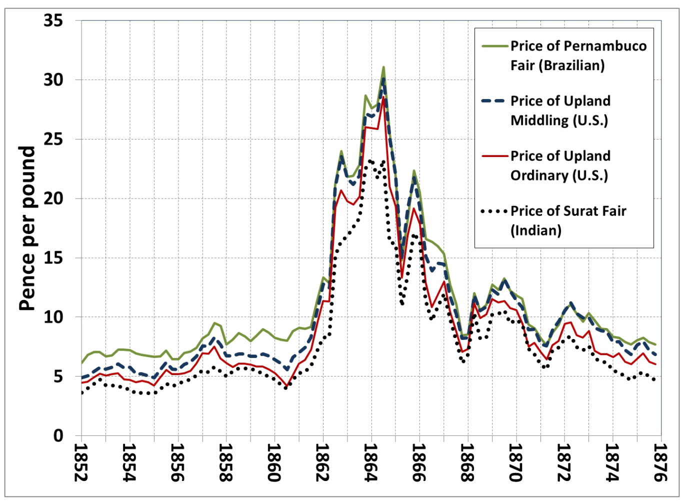
Hypothesis 4: Directed technical change towards Indian cotton more than offset the effect of the increase in relative supply such that the relative price of Indian cotton increased even though it was relatively more abundant.

Hypothesis 3 corresponds to the prediction of the theory when $\sigma_l = 2$, while

Hypothesis 4 corresponds to the prediction when $\sigma_l > 2$. Both of these can be evaluated by observing the time-path of the relative price of Indian cotton.

I begin my investigation by plotting, in Figure 7, the prices of Indian, Brazilian, higher-quality U.S., and lower-quality U.S. cotton in levels.[43] In all periods, these prices are roughly ordered according to quality, with Brazilian (Pernambuco) fetching the highest price, and Indian cotton the lowest. The onset of the Civil War was followed, with some lag, by a sharp increase in the price of all cotton varieties. Prices remained high through 1865 and the began to decline in 1866, though they did not attain their pre-war levels until well into the 1870s.

Figure 7: Raw cotton prices on the Liverpool market for key varieties 1852-1875



Quarterly price data from *The Economist*. Upland Middling is the benchmark higher-quality U.S. cotton variety, Upland Ordinary is a benchmark lower-quality U.S. variety, Surat is the benchmark Indian cotton variety, and Pernambuco is the benchmark Brazilian cotton.

What we cannot see in the previous graph is the behavior of relative prices, which is our primary interest. These relative prices are presented in Figure 8, together with the import quantities for each variety, where Indian and Brazilian cotton are each shown relative to the price of the most comparable U.S. variety. The graphs look almost identical if I compare all of the alternatives to the same variety of U.S. cotton (see Appendix). The price of Indian relative to lower-quality U.S. cotton was

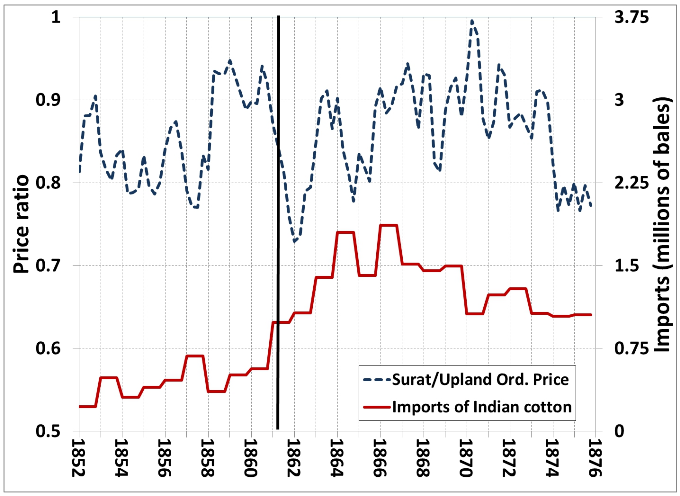
[43] In keeping with the model, I will focus only on these four varieties. In the Appendix I show that the behavior of Egyptian cotton prices is similar to that of Brazilian.

unusually low in 1861-1862, the first two years of the war, and a period in which Indian cotton had become relatively more abundant. However, starting in 1863, there was an increase in the relative price of Indian cotton. This upward trend lasted through the early 1870s, despite the fact that the relative quantity of Indian cotton remained higher than prior to 1861. In contrast, the relative price of Brazilian to U.S. cotton fell in 1861-1862 and remained low through 1876, a period during which the relative abundance of Brazilian cotton was high. The patterns observed in Brazilian cotton prices is consistent with what the model would predict in the absence of significant biased technological progress, given the increase in the relative abundance of these varieties after 1861. In contrast, the initial decrease in the relative price of Indian cotton, followed by the increase after 1863, when a significant number of new technologies tailored to the use of Indian cotton were becoming available, is consistent with the strong induced-bias hypothesis.

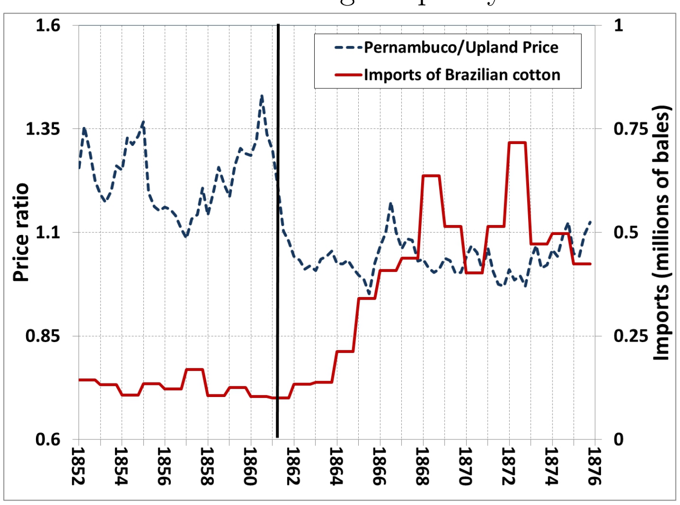
One potential concern with these figures is that there is evidence of an increase in the relative price of Indian cotton in 1858, prior to the Civil War. This increase was due to the short-term effect of the Indian Mutiny (May 1857-1859) which caused a sharp short-term reduction in the availability of Indian cotton (from 680,500 bales in 1857 to 361,000 in 1858). This reduction in supply had the expected short term positive effect on relative prices. It is interesting that the relative price of Indian cotton during this period of shortage is similar to that reached in the late Civil War period even though the quantity of Indian cotton on the market was much higher, reaching 1,866,610 bales in 1866 compared to 361,000 in 1858. Given the shortage of U.S. cotton the increase in the relative quantity of Indian cotton was even greater.

Figure 8: Cotton prices relative to the benchmark U.S. variety and import quantities

Relative price of Indian cotton to lower quality U.S. cotton (Upland Ordinary)



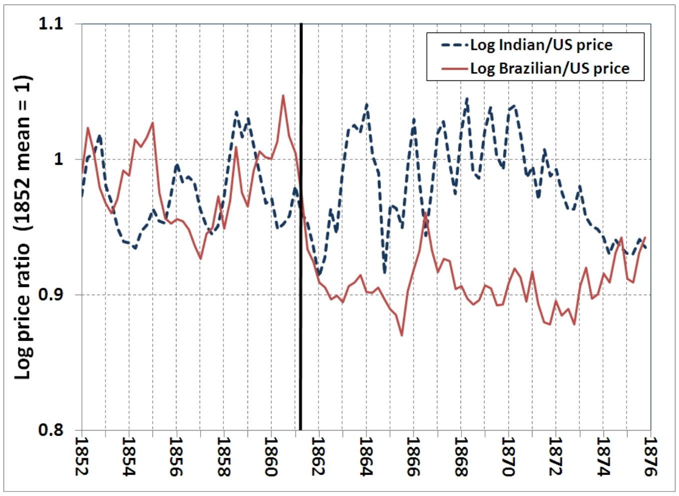
Relative price of Brazilian cotton to higher quality U.S. cotton (Upland Fair)



Price data gathered from *The Economist* magazine.

Figure 9 facilitates comparison between movements in the relative price of Indian and Brazilian cotton by plotting the log relative prices of Indian cotton and Brazilian cotton, with the mean value in 1852 set to one. We can see that the relative prices move within a similar range prior to 1861 (though they do not move together), and that they fall together in 1861, but these relative prices diverge after 1862, with Indian gaining relative to the others. I argue that this divergence is due to the upward pressure on the relative price of Indian cotton exerted by increasing demand caused by the availability of better machines for processing Indian cotton. It is also interesting that this difference fades in the mid-1870's, which suggests that the influence of the inventions generated during 1861-1865 had faded a decade later.

Figure 9: Comparing movement of relative Indian and Brazilian cotton prices



Price data gathered from The Economist magazine.

Constructing a statistical test of these hypothesis is made difficult by the non-linear nature of the predictions as well as uncertainty about the time-frame in which new technologies begin influencing the market. The main econometric approach I take to this problem involves pooling the relative price data from Indian and Brazilian cotton and using,

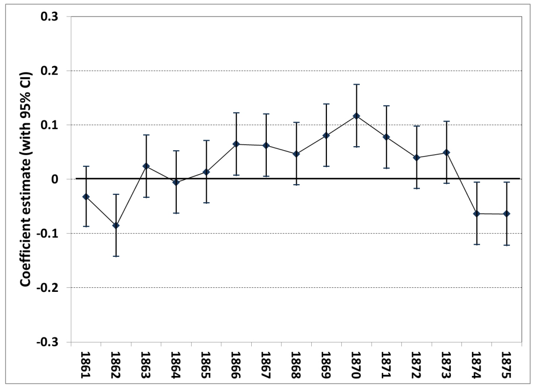
$$\log(RP_{it}) = \alpha + \sum_{k=1861}^{1875} \beta^{I}_{ik} \times IN_i + \sum_{k=1861}^{1} 875\beta^{B}_{ik} \times BR_i + IN_i + BR_i + \gamma MUTINY_{it} + \epsilon_{it}$$

where i designates either Indian or Brazilian cotton, RP_{it} is the price of the variety relative to the comparable U.S. variety, IN_i and BR_i are indicator variables for India and Brazil, respectively, and $MUTINY_{it}$ is an indicator variable for India in 1858-1859 that is used to control for the impact of the Indian Mutiny on the relative price of Indian cotton. This equation is estimated using FGLS while allowing for correlation across panels, heteroskedasticity within panels, and AR1 serial correlation with serial correlation parameters specific to each panel.

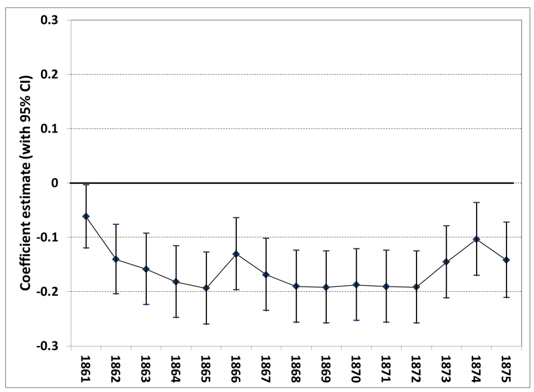
The resulting coefficient estimates are shown graphically in Figure 10, while full regression results are available in the Appendix. The top panel shows the coefficient estimates and 95% confidence intervals for Indian cotton, while the bottom panel does the same for Brazilian cotton. The sharp drop in relative prices for both varieties in 1861-1862 appears to confirm Hypothesis 1. Hypothesis 2 is confirmed by Table 7, which shows results for a series of Wald tests of the difference between the estimated coefficients for Indian and Brazilian cotton. Figure 10 also appears to confirm Hypothesis 3, since there is no evidence of a fall in the relative price of Indian cotton in the years after 1862, at least until 1874. Finally, Figure 10 also offers some support for Hypothesis 4, since we observe positive coefficients for Indian cotton in all but one year from 1863-1873 with statistically significant increases in five of those years.

Figure 10: Estimated impact on the relative price of Indian and Brazilian cotton by year

Estimated coefficients and 95% confidence intervals for Indian cotton



Estimated coefficients and 95% confidence intervals for Brazilian cotton



Estimated coefficients and 95% confidence intervals generated using FGLS regressions on quarterly data from 1852-1875. Standard errors are heteroskadasticity robust, allow for correlation across panels and AR1 serial correlation within panels with panel-specific serial correlation parameters.

Table 7: Wald tests for difference between Indian and Brazilian coefficients

	1861	1862	1863	1864	1865	1866	1867	1868
Chi-sq	0.53	1.59	16.9	15.6	21.5	19.1	26.73	28.1
p-value	0.47	0.21	0.00	0.00	0.00	0.00	0.00	0.00

	1869	1870	1871	1872	1873	1874	1875
Chi-sq	37.2	35.1	40.0	36.3	18.9	0.08	2.86
p-value	0.00	0.00	0.00	0.00	0.00	0.37	0.09

The results above provide evidence in favor of the strong induced-bias hypothesis operating for Indian cotton. There is no evidence that a similar effect occurred for Brazilian cotton. This makes sense given that I have observed technical change which was focused primarily on using Indian cotton.

One potential caveat to this analysis is that the prices used are those on the Liverpool market, rather than farm-gate prices. Thus, they may reflect quality improvements in Indian cotton resulting from the new technologies which took place before the cotton reached the Liverpool market.[44] However, there are two reasons to think that this is not an important concern. First, the prices I use are for benchmark cotton varieties which are supposed to be for a constant quality level, so quality improvements should not be reflected in these prices. Second, using additional data described in Appendix A.12, I show that the London price of Indian cotton closely tracks the price in Bombay, the major Indian export market, suggesting that there was no change in the gap between these prices induced by quality differences.

7 Evaluating the theory

Thus far we have seen that the U.S. Civil War decreased the relative supply of U.S. cotton to Britain and that there was a corresponding increase in innovative activity related to alternative cotton supplied from India. Despite the increase in the relative supply of Indian cotton on the market during and after the war, there was no appreciable decrease in the long-run relative price of Indian cotton, and there is some evidence that the relative price may have actually increased. In contrast, I found little evidence of technical change directed towards Brazilian cotton and I observe a clear decrease in the relative price of Brazilian cotton in both the short and long-run, corresponding to the increase in the relative quantity of that variety.

Can these patterns be explained by the theory? In order to answer this question I need estimates of the elasticity of substitution between the various cotton varieties. Given these elasticities, the predictions of the theory are known and can be compared to the results described in the two preceding sections. In this section I begin by estimating the relevant elasticities using an approach based on the Almost Ideal

[44]The cotton could have benefited from processing by improved machines on its way from India, particularly since most ginning was done in the exporting country.

Demand System (AIDS), which has been used by previous studies. I then discuss some potential drawbacks of that approach. Finally, I generate additional estimates, based on the model offered in this paper, which addresses some of the concerns with the estimates generated using the AIDS approach.

One approach to estimating the elasticity of substitution between inputs is to use a linear approximation to the Almost Ideal Demand System (AIDS) introduced by Deaton & Muellbauer (1980). This approach has previously been applied to the cotton textile industry in the 19th century by Irwin (2003), and readers are referred to that paper for additional details on this approach. The main advantage of the AIDS approach is that it involves a flexible and general demand system which nests a variety of other demand systems. In particular, it is more general than the nested CES demand system used in my theory.

The estimating equation for the AIDS approach is,

$$w_{it} = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ \ln(c_{jt}) + \beta_i \ \ln(D_t/C_t) + u_t$$

where w_{it} is the expenditure share of input type i, c_{jt} is the price of input j, D_t is total expenditure on all inputs, C_t is a price index over all inputs, and u_t is a disturbance term. For empirical applications, the input price index is generally approximated by,

$$ln(C_t) = \sum_{k=1}^{n} w_{kt} \ \ln(c_{kt}) \ .$$

Given the estimated coefficients from these equations, the elasticity of substitution between any two input types can be calculated according to $\sigma_{ij} = 1+\gamma_{ij}/(w_i w_j)$, where the corresponding standard error is the estimated standard error for γ_{ij} divided by $w_i w_j$.

Estimating these equations requires the prices and import quantities for each input variety on the British market. Separate import quantity data are not available for higher and lower-quality U.S. cotton, so I am able to calculate only an overall elasticity of substitution between each alternative variety and all U.S. cotton. Later, I will discuss the direction of bias introduced by combining different types of U.S. cotton. Following Irwin (2003), I estimate these equations using seemingly unrelated regressions while imposing symmetry ($\gamma_{ij} = \gamma ji$). In estimating these equations it is necessary to drop one and so I drop the equation for Egyptian cotton, the fourth largest variety.

Table 8 presents elasticity of substitution estimates generated using the AIDS approach for a variety of data sources and time periods. The full results from the regressions used to generate these values are available in the Appendix. The first column of Table 8 reproduces results found in Irwin (2003) using data from Mann (1860). The remaining columns present new estimates generated using data from Ellison (1886) for a variety of time periods. The most relevant are in Columns 2 and 3, which present results for the twenty-year periods just before and just after the war. Both of these suggest that the elasticity of substitution between U.S. and Indian cotton was above 1 and likely also above 2. The elasticity of substitution between U.S. and Brazilian cotton also appears to be above 1, and some specifications generate point estimates that are above 2. There is little evidence of substitution between Indian and Brazilian cotton.

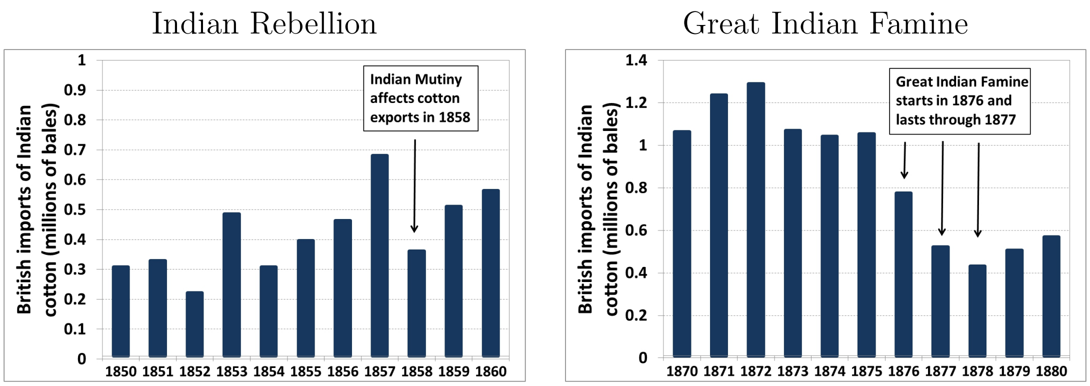
Table 8: Elasticity of substitution estimates generated using the AIDS approach

	Irwin (2001)	Additional estimates			
Data source:	Mann	Ellison	Ellison	Ellison	Ellison
Years:	1820-1859	1840-1859	1865-1884	1820-1859	1820-1884
U.S.-India	1.96	2.19	2.38	1.58	1.32
	(0.80)	(1.26)	(0.97)	(1.28)	(1.14)
U.S.-Brazil	3.88	2.95	1.66	4.16	5.39
	(0.70)	(0.73)	(3.06)	(0.70)	(1.27)
India-Brazil		-0.97	0.24	-0.01	-0.79
		(4.02)	(4.83)	(3.85)	(4.50)

The results shown in Table 8 are likely to suffer from three sources of bias. First, the AIDS approach assumes that export supplies are perfectly elastic. In fact, the supply curves for these varieties are clearly upward sloping. Ignoring this will bias the elasticity estimates downwards. Second, the estimates in Table 8 were generated while pooling higher and lower-quality U.S. cotton. Yet the relevant elasticity of substitution for evaluating the theory is between Indian and lower-quality U.S. cotton (or Brazilian and higher-quality U.S. cotton). Since these are more similar varieties, the elasticities of substitution that are relevant for the theory must be higher than those shown in Table 8. Finally, these estimates ignore the possibility of directed technical change. From Acemoglu (2002), we know that regardless of the elasticity of substitution, an increase in the relative supply of one input generates technical change that is biased towards that input. Thus, if directed technical change is taking place, this will bias the estimated elasticities of substitution shown in Table 8 upwards. Of the sources of bias present in the AIDS estimates, the most troubling is the potential bias due to directed technical change, which may cause the estimates in Table 8 to overstate the true short-run elasticities of substitution.

One way to address the shortcomings of the AIDS elasticity estimates is to use an exogenous shock that generate large short-run changes in the relative quantities of available cotton varieties and observe how these shifts are reflected in relative prices. Specifically, I will exploit two large shocks to the quantity of cotton produced in India. The first was the Indian Rebellion, a large revolt by Indian soldiers from May 1857 to 1859. While the revolt was eventually crushed by the British administration, it caused a massive disruption to economic activity which is reflected by a sharp drop in exports of Indian cotton in 1858. The left-hand panel of Figure 11 describes the impact of this event on relative quantities and relative prices. The second event I exploit is the Great Indian Famine of 1876-1878. This drought-driven famine cost millions of lives and sharply disrupted cotton supplies from India during the famine years. The right-hand panel of Figure 11 describes the impact of the famine on relative quantities. The distinguishing features of both of these events are that they were unexpected, they were of short duration, and they significantly reduced the availability of Indian cotton. In addition, I will also show results in which I consider the impact of the change in relative quantities on relative prices during the first two years of the Civil War, though given the longer-run nature of this shock I consider these estimates to be less relevant.

Figure 11: Impact of shocks on Indian cotton exports to Britain



Data from Ellison (1886)

Because this approach exploits short-run variations, it will avoid bias due to directed technical change. Moreover, if the shock to relative quantities is large and rapid, any bias generated by quantities responding to price changes should be small in relation. This is because the ability of relative quantities to respond to price changes will be constrained in the short run and small relative to the changes generated by the shock. The main constraint in implementing this approach is that large shocks of the type I need are relatively rare so few data points are available. As a result, I view this approach as complementary to the estimates presented in Table 8.

For all of these events I will use a simple time-series instrumental-variables estimation strategy. For both events, I will use data from the year in which the disruption occurred as well as a number of years before. I will not include data from the period after the event, since these years may be affected by ongoing effects of the event. So when looking at the Indian Mutiny, I use data from 1852-1858. For the Great Indian Famine, I use data from 1867-1877. For the Civil War shock I use data from 1852-1862. In each case, the instrument will be an indicator variable for the year(s) in which the event affected economic activity (1858 for the Mutiny, 1876-77 for the Great Famine, and 1861-1862 for the Civil War). Thus, the estimating equation will be,

$$\log(c_{I,t}/c_{USL,t}) = \beta_0 + \beta_1 \log(Z_{I,t}/Z_{US,t}) + \beta_3 TT_t + \epsilon_t \ ,$$

and the first-stage regression is,

$$\log(Z_{I,t}/Z_{US,t}) = \gamma_0 + \gamma_1 EVENT_t + \gamma_3 TT_t + e_t$$

where $EVENT_t$ is an indicator variable for the year in which the disruption occurred and TT_t is a time-trend. Given estimates of β_1, I can back out the elasticity of substitution between Indian and U.S. cotton using $\beta_1 = -1/\sigma_l$ from Equation 6. The final potential source of bias in these estimates is that I cannot separately identify the level of low-quality and high-quality U.S. cotton imports and I use total U.S. imports as the denominator in calculating relative quantities. This will impart an upward bias in my estimate of β_1 and therefore a downward bias in the estimated elasticity of substitution.

The results are presented in Table 9. In all cases, the point estimate of the elasticity of substitution is above two, and the 95% confidence interval for the estimates is also generally above 2 and always above 1. The Durbin-Watson statistics suggest that serial correlation is not a major concern. However, we may be somewhat worried that the instruments are weak. The first stage regression results show that while the coefficient estimates in the key event instruements are large, they are generally only statistically signficant at around the 85% confidence level. This is not surprising given the rough nature of the instruments.

This section has presented two very different approaches to estimating the elasticity of substitution between Indian and U.S. cotton. While the AIDS approach has the advantage of a very flexible demand system and uses a much larger set of data, it may also be susceptible to several sources of bias. In contrast, using short-term shock to identify the elasticity of substitution avoids these sources of bias, but these results are based on a much more restricted set of observations. Despite these differences, both approaches consistently suggest that the elasticity of substitution between Indian and U.S. cotton is above 1 and in most cases I find evidence that the elasticity was also above 2.

Given these findings, the model predicts that the during the Civil War we should observe (1) technical change directed towards technologies which augmented Indian cotton and (2) no decrease, and perhaps an increase, in the relative price of Indian to U.S. cotton. Thus, the model appears to correctly predict the results described in

Sections 5.2 and 6.

Table 9: Elasticity of substitution estimates generated using exogenous shocks

	DV: Relative price of Indian to low-quality U.S. cotton		
	Rebellion	Famine	Civil War
$\log(Z_{It}/Z_{US,t})$	-0.151***	-0.313**	-0.168**
	(0.0578)	(0.129)	(0.0675)
TT	0.0164*	-0.0486***	0.0185***
	(0.00852)	(0.0170)	(0.00618)
Constant	-0.465***	0.745**	-0.496***
	(0.108)	(0.312)	(0.121)
Observations	7	8	10
R-squared	0.381	0.262	0.599
Data years:	1852-1858	1870-1877	1852-1862
Shock period:	1858	1876-1877	1861-1862
Durbin-Watson:	2.52	2.24	2.69
First-stage regression results			
$EVENT_t$	-0.861	-0.51	0.638
	(0.457)	(0.275)	(0.463)
TT_t	0.179*	-0.043	0.369
	(0.08)	(0.051)	0.048
Constant	-2.04**	0.44	-1.63**
	(0.311)	1.12	(0.272)
F-stat	2.72	7.51	2.46
Implied elasticity of substitution between Indian/U.S. cotton			
Estimate	6.62	3.19	5.95
95% CI	(3.8,26.4)	(1.76,16.72)	(3.32,27.93)

8 Conclusions

This study shows that a large exogenous change in the cost of providing inputs for the 19th century British cotton textile industry led to (1) directed technical change in favor of one input – Indian cotton – which had become relatively more abundant and (2) input price movements consistent with the strong induced-bias hypothesis for this input. Given my elasticity estimates, these results are consistent with the predictions of the directed technical change model of Acemoglu (2002). This provides us with some confidence in the ability of this model to explain the process of technical change and how it is influenced by the the cost of providing inputs to production. The results of this study lend support to the wide set of theories applying the idea of directed technical change. While my results cannot tell us whether directed technical change is operating in any particular setting, they lend plausibility to arguments based on these mechanisms, by providing clearer evidence than was previous available that directed technical change does occur and can meaningfully influence market conditions.

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A Appendix

A.1 Most innovative technology categories by patent count

Table 10: Top ten British Patent Office (BPO) tech. categories 1855-1883

Rank	Technology Category	No. Patents	Rank	Technology Category	No. Patents
1	Metals, Cutting, etc	7,017	6	Railway etc. vehicles	4,184
2	Furnaces	6,157	7	Steam generators	4,065
3	Spinning	6,009	8	Furniture	3,216
4	Steam engines	4,809	9	Mechanisms	3,120
5	Weaving	4,807	10	Ships, Div. I (fittings, etc.)	3,051

Top ten technology categories, by patent count, out of the 146 total British Patent Office technology categories. "Spinning" includes machinery used in the preparatory and spinning stages of production. "Weaving" includes machinery used in the weaving and finishing stages.

A.2 Definitions of important textile terms

The following definitions were constructed with the aid of *The "Mercury" Dictionary of Textile Terms*. 1950. Textile Mercury Limited: Manchester, England.

Bolls- The seed pod of cotton and has from three to five cells, each of which contains from six to twelve seeds, the seeds being covered with cotton fibers.

Carding- A very thorough opening-out and separating of the fibers of cotton, together with an effective cleaning. This machine is the last where cleaning the cotton takes place (unless the cotton has to be combed).

Combing- This term is used literally and denotes the combing of fibrous materials in sliver form by mechanically actuated combs or by hand-operated combs. In general, the objects in combing are two, namely (1) to obtain the maximum parallelization of the fibers and (2) to remove impurities and undesired short fibers.

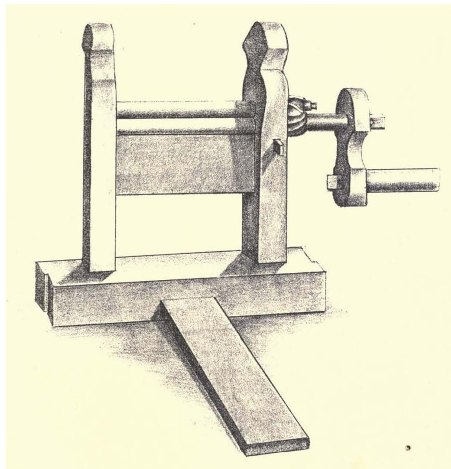
Gin- A cotton cleaning machine with the primary purpose of separating the cotton seeds from the cotton fibers.

Opening cotton- This is done on machines (openers) which beat the cotton into a more fleecy condition and also remove a good proportion of the dirt and heavier impurities.

Scutching- An operation in preparing cotton for spinning that has three objects, to reduce the cotton to a loose open condition by beating it, removal of impurities remaining in the cotton after opening, and the formation of a continuous lap or web of cotton wound on to a rod–which laps go forward to the carding engine.

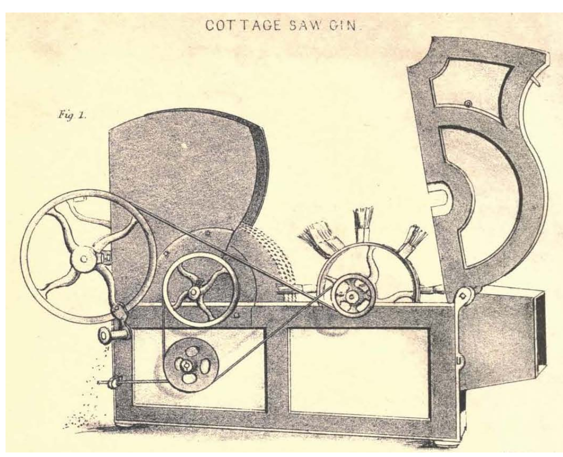
A.3 Machines for ginning cotton

Figure 12: Indian Churka for removing cotton seeds



Reproduced from Wheeler (1862).

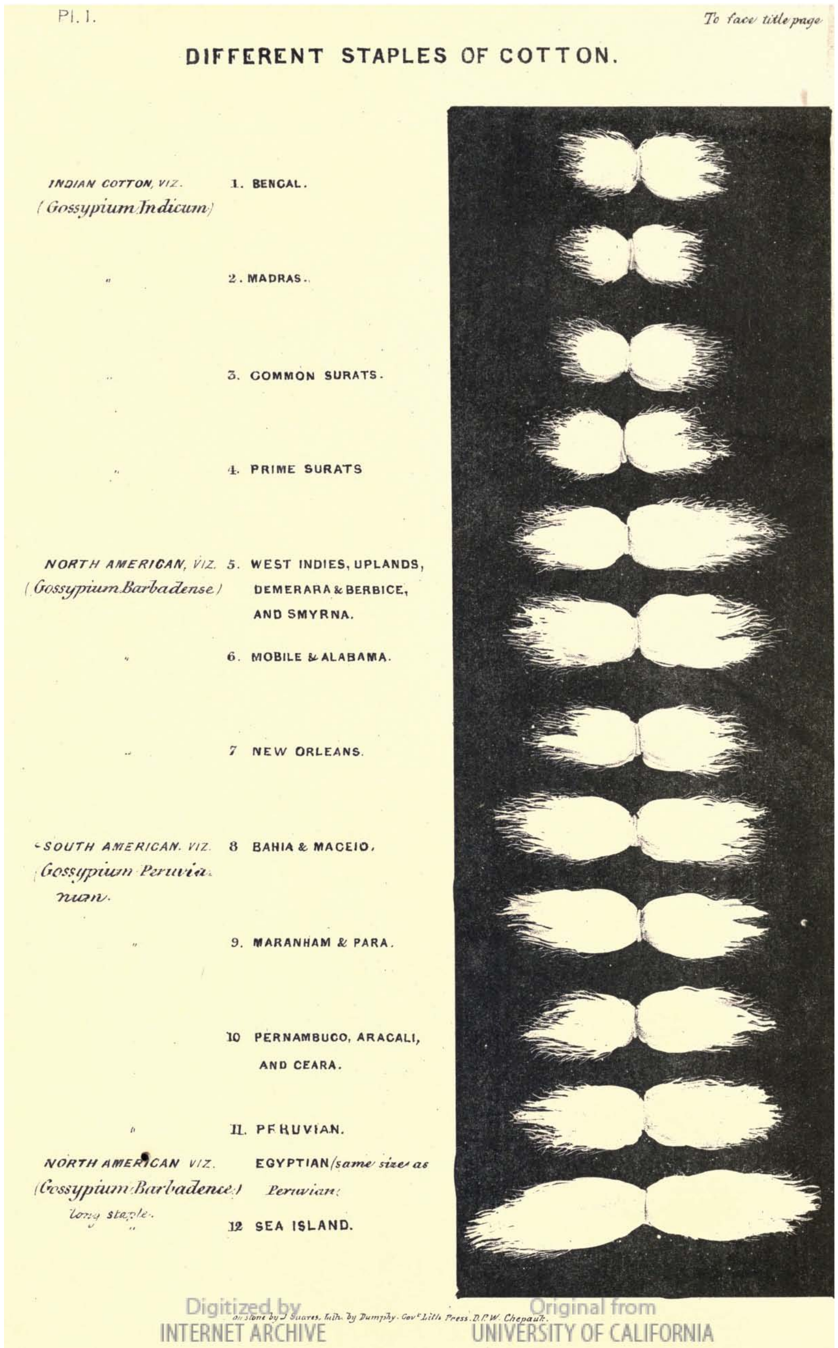
Figure 13: Cottage Saw Gin



Reproduced from Wheeler (1862).

A.4 Details on the differences between cotton types

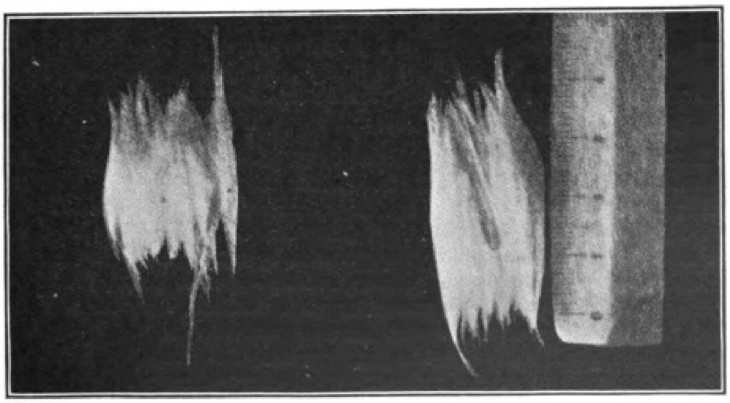
Figure 14: Length of cotton staples for various cotton types



Reproduced from Wheeler (1862).

A.5 Impact of ginning on cotton fiber length

Figure 15: A comparison of ginned (left) and hand-cleaned cotton (right) fiber length

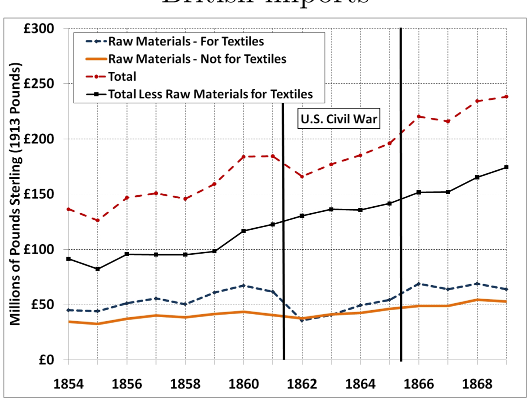


Reproduced from Pearse (1921).

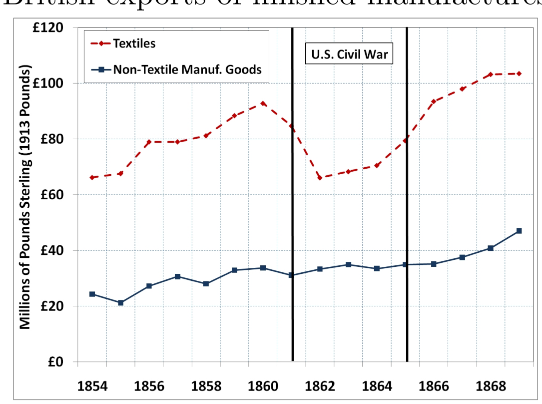
A.6 Background graphs

Figure 16: British imports and exports 1851-1869

British imports



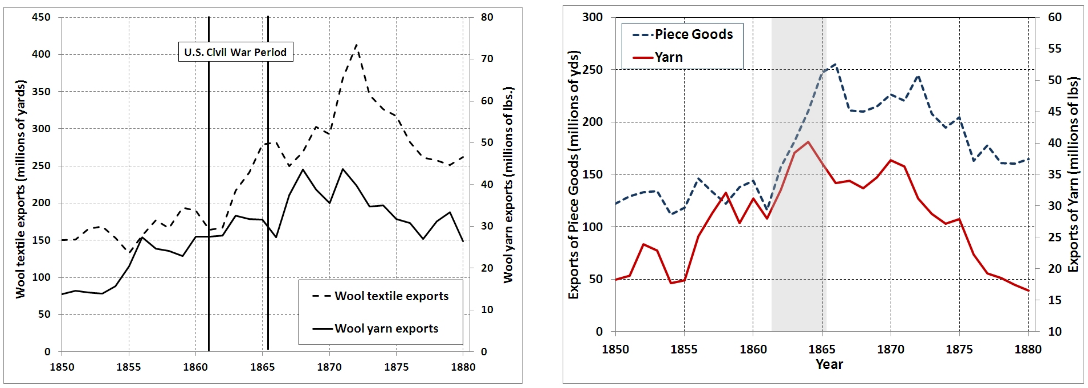
British exports of finished manufactures



Data from Mitchell & Deane (1962).

Figure 17: British wool and linen textile exports 1815-1910

Wool textile exports　　　　　　Linen textile exports



Data from Mitchell & Deane (1962)

A.7 Theory appendix

This appendix presents additional details related to the theoretical model.

Derivation of Equation 12

To derive Equation 12 I begin by noting that the CES demand structure implies the following relationship between the price and quantity indices in the low and high-quality market segments:

$$\frac{P_L}{P_H} = \left(\frac{Y_L}{Y_H}\right)^{\frac{-1}{\epsilon}}. \tag{14}$$

I will substitute in for Y_L, Y_H, P_L, and P_H using the definitions for each of these terms given in the text. But first I want to write each of these price and quantity indices in terms of technologies and input quantities. Beginning with the price index for the low-quality market segment, I use $V_i = \beta p_i^{1/\beta} Z_i / r$ to write,

$$P_L = \left(\frac{r}{\beta}\right)^{\beta} V_I^{\beta} Z_I^{-\beta} \left[1 + \left(\frac{Z_{USL}}{Z_I}\right)^{-\beta(1-\rho_l)} \left(\frac{V_{USL}}{V_I}\right)^{\beta(1-\rho_l)}\right]^{\frac{1}{1-\rho_l}}.$$

A similar equation holds for the high-quality market segment. Taking the ratio of these, I have,

$$\frac{P_L}{P_H} = \left(\frac{V_I}{V_B}\right)^{\beta} \left(\frac{Z_I}{Z_B}\right)^{-\beta} \frac{\left[1 + \left(\frac{Z_{USL}}{Z_I}\right)^{-\beta(1-\rho_l)} \left(\frac{V_{USL}}{V_I}\right)^{\beta(1-\rho_l)}\right]^{\frac{1}{1-\rho_l}}}{\left[1 + \left(\frac{Z_{USH}}{Z_B}\right)^{-\beta(1-\rho_l)} \left(\frac{V_{USL}}{V_I}\right)^{\beta(1-\rho_l)}\right]^{\frac{1}{1-\rho_l}}} .$$

In the long-run balanced growth path it must be that $V_i/V_j = 1$ for all i and j and Equation 9 must hold. Using these, I have,

$$\frac{P_L}{P_H} = \left(\frac{Z_I}{Z_B}\right)^{-\beta} \frac{N_I^{\frac{-1}{1-\rho_l}}}{N_B^{\frac{-1}{1-\rho_h}}} \frac{[N_I + N_{USL}]^{\frac{1}{1-\rho_l}}}{[N_B + N_{USH}]^{\frac{1}{1-\rho_l}}} . \tag{15}$$

To solve for the relative quantity indices, I use, Equation 4 and $V_i = \beta p_i^{1/\beta} Z_i/r$ to write,

$$y_i = \frac{1}{1-\beta} \left(\frac{r}{\beta}\right)^{1-\beta} V_i^{1-\beta} Z_i^{\beta} N_i .$$

Plugging this into the low-quality market segment output index I obtain,

$$Y_L = \frac{1}{1-\beta} \left(\frac{r}{\beta}\right)^{1-\beta} V_I^{1-\beta} Z_I^{\beta} \left[N_I^{\frac{\rho_l-1}{\rho_l}} + N_{USL}^{\frac{\rho_l-1}{\rho_l}} \left(\frac{V_{USL}}{V_I}\right)^{\frac{(1-\beta)(\rho_l-1)}{\rho_l}} \left(\frac{Z_{USL}}{Z_I}\right)^{\frac{\beta(\rho_l-1)}{\rho_l}}\right]^{\frac{\rho_l}{\rho_l-1}}$$

A similar expression holds for the high-quality market segment. Taking the ratio of these, I obtain,

$$\frac{Y_L}{Y_H} = \left(\frac{V_I}{V_B}\right)^{1-\beta} \left(\frac{Z_I}{Z_B}\right)^{\beta} \frac{\left[N_I^{\frac{\rho_l-1}{\rho_l}} + N_{USL}^{\frac{\rho_l-1}{\rho_l}} \left(\frac{V_{USL}}{V_I}\right)^{\frac{(1-\beta)(\rho_l-1)}{\rho_l}} \left(\frac{Z_{USL}}{Z_I}\right)^{\frac{\beta(\rho_l-1)}{\rho_l}}\right]^{\frac{\rho_l}{\rho_l-1}}}{\left[N_B^{\frac{\rho_h-1}{\rho_h}} + N_{USH}^{\frac{\rho_h-1}{\rho_h}} \left(\frac{V_{USH}}{V_B}\right)^{\frac{(1-\beta)(\rho_h-1)}{\rho_h}} \left(\frac{Z_{USH}}{Z_B}\right)^{\frac{\beta(\rho_h-1)}{\rho_h}}\right]^{\frac{\rho_h}{\rho_h-1}}}$$

In the long-run balanced growth path, $V_i/V_j = 1$ for all i and j and Equation 9 holds. Using these, I have,

$$\frac{Y_L}{Y_H} = \left(\frac{Z_I}{Z_B}\right)^{\beta} \frac{N_I^{\frac{-1}{\rho_l-1}}}{N_B^{\frac{\rho_h-1}{\rho_h}}} \frac{[N_I + N_{USL}]^{\frac{\rho_l}{\rho_l-1}}}{[N_B + N_{USH}]^{\frac{\rho_h}{\rho_h-1}}} \tag{16}$$

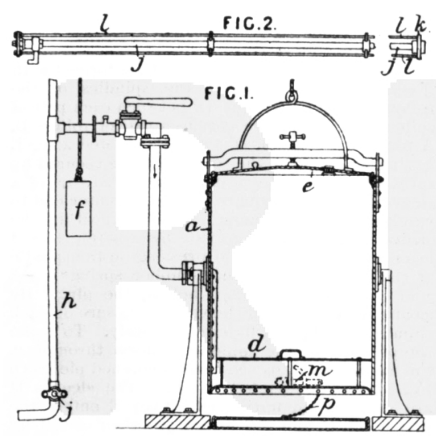
Finally, I plug Equations 15 and 16 into Equation 14 and reorganize in order to obtain Equation 12.

A.8 Example patent specifically mentioning Indian cotton

Figure 18: An Example: Patent No. 2162 from 1862

2162. Wanklyn, W. July 30.

Steaming fibres ; openers, cleaners, &c.—Relates to apparatus for opening and conditioning East Indian and other tightly-compressed cotton, sheep's wool, &c. by steaming. The cotton is transferred from the bale to a vessel *a*, which is mounted on trunnions, and is provided with a perforated false bottom *d* and a tightly-fitting lid *e* balanced by the counterweight *f*. Steam under pressure is admitted to the space below the perforated false bottom, and after the material has been submitted to the action of the steam for about a minute, the steam is shut off, the lid *e* removed and the vessel *a* tilted so that the cotton may be raked into a truck &c. and taken to the opening-machine. A suitable prop is provided for holding the vessel *a* in the tilted position, and the act of tilting the vessel opens by means of a chain *p* an escape valve *m* for condensed water. In order that condensed water may be excluded as much as possible from the vessel *a*, the steam pipe *h* is connected with a horizontal pipe *j* in which is a valve connected by rods *l* with a crosshead *k* on the end of the pipe. So long as the pipe *j* is sufficiently heated by the steam, the valve is closed, but when the pipe is cooled by the accumulated condensed water, the valve is opened and the water escapes.



From *British Patent Abstracts, Class 120, 1855-1866.* Available from the British Library.

A.9 Details of patent title search results

Summary statistics for these patent title search results are provided in Table 11. We can see that the majority of those patents listing one of the main textile inputs (cotton, wool, linen, silk) are classified into the BPO spinning technology category, while a few are listed in the weaving category, and some others fall into categories other than spinning and weaving. As a quality check, keyword searches were also used to identify those patents with "spinning" or "weaving' in the title. Most patents with spinning in the title are listed in the BPO spinning category, while most of those mentioning weaving are classified in the BPO weaving category. This suggests that the keyword search approach is reliable, though more restrictive, than the BPO categories.

Table 11: Summary statistics from patent title keyword searches, 1855-1870

Title search term:	Total patents	Number in BPO Spinning	Share in BPO Spinning	Share of BPO Spinning	Number in BPO Weaving	Share in BPO Weaving	Share of BPO Weaving
Cotton	1,230	892	73%	29%	61	5%	2%
Wool	998	651	65%	21%	57	6%	2%
Linen	518	397	77%	13%	21	4%	1%
Silk	392	279	71%	9%	36	9%	1%
Spinning	976	935	96%	30%	25	3%	1%
Weaving	1,245	42	3%	1%	1,200	96%	46%

Patents are identified by searching for each title search term, e.g., "cotton", in the patent titles.

A.10 Regression results for the impact of the shock on overall cotton textile innovation

This section establishes the patterns described in Section 5.1 more rigorously. I will take two approaches. First, I want to establish that there is something unusual happening in the cotton textile industry during the shock period relative to the other textile industries. To do so, I pool the data four all four textile industries ($i \in \{Cotton, \ Wool, \ Linen, \ Silk\}$) and run a panel regression using,

$$\log(P_{it}) = \sum_{i=1 \in I} \gamma_i \times S_t \times I_i + \phi_i + \xi_t + TT_{it} + Q_t + \epsilon_{it},$$

where P_{it} is the log count of patents in industry i and period t, S_t is an indicator variable for the shock period (Q2 1861 - Q1 1865), I_i is an indicator variable for industry i, ϕ_i is a full set of industry-specific fixed effects, TT_{it} is a full set of industry-specific time trends, ξ_t is a set of indicator variables for each year outside of the shock period, and Q_t is a set of quarter indicator variables (to control for seasonal effects). This regression is run on quarterly data from 1853-1870. To avoid colinearity, the indicator variables for the first year and the first quarter are omitted. Regression results are generated using feasible generalized least squares (FGLS) approach while allowing for heteroskedasticity at the panel level, correlated errors across panels, and AR1 serial correlation with serial correlation parameters specific to each panel.[45]

Results are shown in Table 12. We can see that in all of these specifications the level of patents related to cotton textiles is high during the shock period relative to

[45]Note that I observe no industry-year bins with zero patents in these data, so there is not a clear need to apply a count data model to this analysis. Nevertheless, I undertake robustness tests with Poisson and Negative Binomial models in the Appendix and show that these approaches yield similar results.

the the three comparator textile industries. In all cases this difference is statistically significant, as highlighted by the F-tests shown in at the bottom of the table.

Table 12: Panel-data regressions across textile industries

	(1)	(2)	(3)	(4)
Cotton x Shock period	0.376***	0.145	0.294**	0.245**
	(0.0858)	(0.103)	(0.118)	(0.113)
Linen x Shock period	-0.128	-0.391**	-0.212	-0.267*
	(0.177)	(0.156)	(0.150)	(0.143)
Silk x Shock period	-0.168	-0.390**	-0.138	-0.185
	(0.184)	(0.166)	(0.142)	(0.138)
Wool x Shock period	-0.0622	-0.294**	-0.154	-0.204*
	(0.107)	(0.129)	(0.120)	(0.120)
Log total non-textile patents				1.282***
				(0.440)
Input TT (p value)			[0.000]	[0.000]
Year effects	No	Yes	Yes	Yes
Quarter effects	No	Yes	Yes	Yes
Observations	288	288	288	288
Number of industries	4	4	4	4
Wald test Cotton x Shock period coefficient equal to:				
Linen x Shock period	9.16	12.55	13.56	14.24
(p value)	(0.003)	(0.000)	(0.000)	(0.000)
Silk x Shock period	9.62	11.06	10.92	11.23
(p value)	(0.002)	(0.001)	(0.001)	(0.001)
Wool x Shock period	21.33	19.01	23.02	23.04
(p value)	(0.000)	(0.000)	(0.000)	(0.000)

FGLS regressions run on quarterly panel data from 1853-1870. Standard errors, shown in parenthesis, are robust to heteroskedasticity, correlation across panels, and AR1 serial correlation with panel-specific serial correlation parameters. All regressions include industry fixed effects. Indicator variables for the first year (1853) and the first quarter are omitted. Indicator variables for the years 1861-1865 are omitted to avoid colinearity.

Next, I want to investigate more carefully the time path of the effect of the shock on innovation in the cotton textile industry. The key question here is whether the difference between what is happening in the cotton textile industry and other industries is driven entirely by patenting that occurred early in the Civil War period. If that were true, we might be concerned that these patterns were driven only by the patenting of existing ideas which became profitable as a result of the changes induced by the war, rather than the development of new innovations. To investigate this I pool data on cotton, wool, linen, and silk technologies and use the following specification,

$$\log(P_{it}) = \sum_{j=1858}^{1868} \gamma_t \times \xi_j \times COTTON + \phi_i + \xi_t + TT_{it} + Q_t + \epsilon_{it},$$

where ξ_j is an indicator variable for year j and $COTTON$ is an indicator variable denoting the cotton textile industry. In this specification, ξ_t is a full set of year indicator variables. I include $\xi_j \times COTTON$ variables for $j \in \{1858,\ 1868\}$ in order to identify patenting patterns in the cotton textile industry up to three years before and after the Civil War period. To avoid colinearity, the indicator variables for the year 1853 and for the first quarter are omitted.

The results presented in Table 13 show that, while there was an immediate spike in patenting in 1861, the largest increases in patenting of cotton textile technologies occur later in the war, in 1863 and 1864.

Table 13: Timing of the response within the cotton textile industry

	(1)	(2)	(3)	(4)
Cotton x 1858	-0.211**	-0.142	-0.134	-0.136
	(0.0845)	(0.128)	(0.116)	(0.116)
Cotton x 1859	-0.183**	-0.138	-0.132	-0.135
	(0.0843)	(0.128)	(0.116)	(0.116)
Cotton x 1860	0.0934	0.142	0.132	0.127
	(0.0843)	(0.128)	(0.116)	(0.116)
Cotton x 1861	0.517***	0.505***	0.510***	0.508***
	(0.0843)	(0.128)	(0.117)	(0.116)
Cotton x 1862	0.400***	0.391***	0.371***	0.369***
	(0.0843)	(0.128)	(0.117)	(0.117)
Cotton x 1863	0.462***	0.589***	0.500***	0.499***
	(0.0843)	(0.128)	(0.118)	(0.118)
Cotton x 1864	0.482***	0.786***	0.705***	0.706***
	(0.0843)	(0.128)	(0.120)	(0.120)
Cotton x 1865	0.244***	0.458***	0.392***	0.391***
	(0.0843)	(0.128)	(0.121)	(0.121)
Cotton x 1866	-0.0509	-0.0216	-0.115	-0.116
	(0.0843)	(0.128)	(0.123)	(0.123)
Cotton x 1867	0.133	0.454***	0.341***	0.342***
	(0.0843)	(0.128)	(0.126)	(0.125)
Cotton x 1868	-0.0306	0.0169	-0.142	-0.146
	(0.0845)	(0.128)	(0.129)	(0.129)
Log total non-textile patents				1.275***
				(0.402)
Input TT (p value)			[0.000]	[0.000]
Year effects	No	Yes	Yes	Yes
Quarter effects	No	Yes	Yes	Yes
Observations	288	288	288	288
Number of industries	4	4	4	4

FGLS regressions run on quarterly panel data from 1853-1870. Standard errors, shown in parenthesis, are robust to heteroskedasticity, correlation across panels, and AR1 serial correlation with panel-specific serial correlation parameters. All regressions include industry fixed effects. Dummy variables for the first year (1853) and the first quarter are omitted.

A.11 Indicators of patent quality

This section describes the three measures of patent quality used to evaluate whether the 1861-1865 period was also characterized by an increase in the number of high-quality cotton-textile-related patents. These measures attempt to account for three aspects of patent quality: (1) long-term viability, (2) wider applicability, and (3) initial novelty. By long-term viability, I mean the extent to which the patented invention remains economically important years after its initial introduction. This aspect will be measured using data on the payment of patent renewal fees. Wider applicability means the breadth of different locations and economic environments in which the invention is used. To measure this aspect, I consider patents by British inventors in India and the U.S. The third aspect, initial novelty, is the extent to which the invention was recognized as a significantly new technological contribution. This aspect will be measured by observing whether patents were described in a contemporary periodical focused on new inventions. While it is reasonable to expect these quality measures to be correlated, it is also possible to think of situations in which they may diverge, which is why multiple measures of patent quality are considered.[46]

A.11.1 Valuing patents using renewal data

During the period covered by this study, British patents lasted for 14 years, but in order to keep them in force patent holders were required to pay renewal fees of £50 before the end of three years and an additional £100 before the end of seven years.[47] These were substantial sums at the time and the result was that the vast majority of patents were allowed to expire before their full term. My data show that just under 18% of patents were renewed at three years, while just over 6% were renewed at seven years. Thus, paying a renewal fee represents a substantial investment which would only have been worth it for a small set of the most successful technologies.

Renewal fee data were gathered from listings in *Mechanics' Magazine*, a weekly periodical focusing on patents and related topics. The magazine is available from the end of 1858 to the end of 1872, so that data on renewals at year three are available for patents filed from 1856-1869 and data on renewals at year seven are available from 1853-1865. By merging the renewal data with the primary patent data set, it is possible to track renewal patterns for textile-related patents.

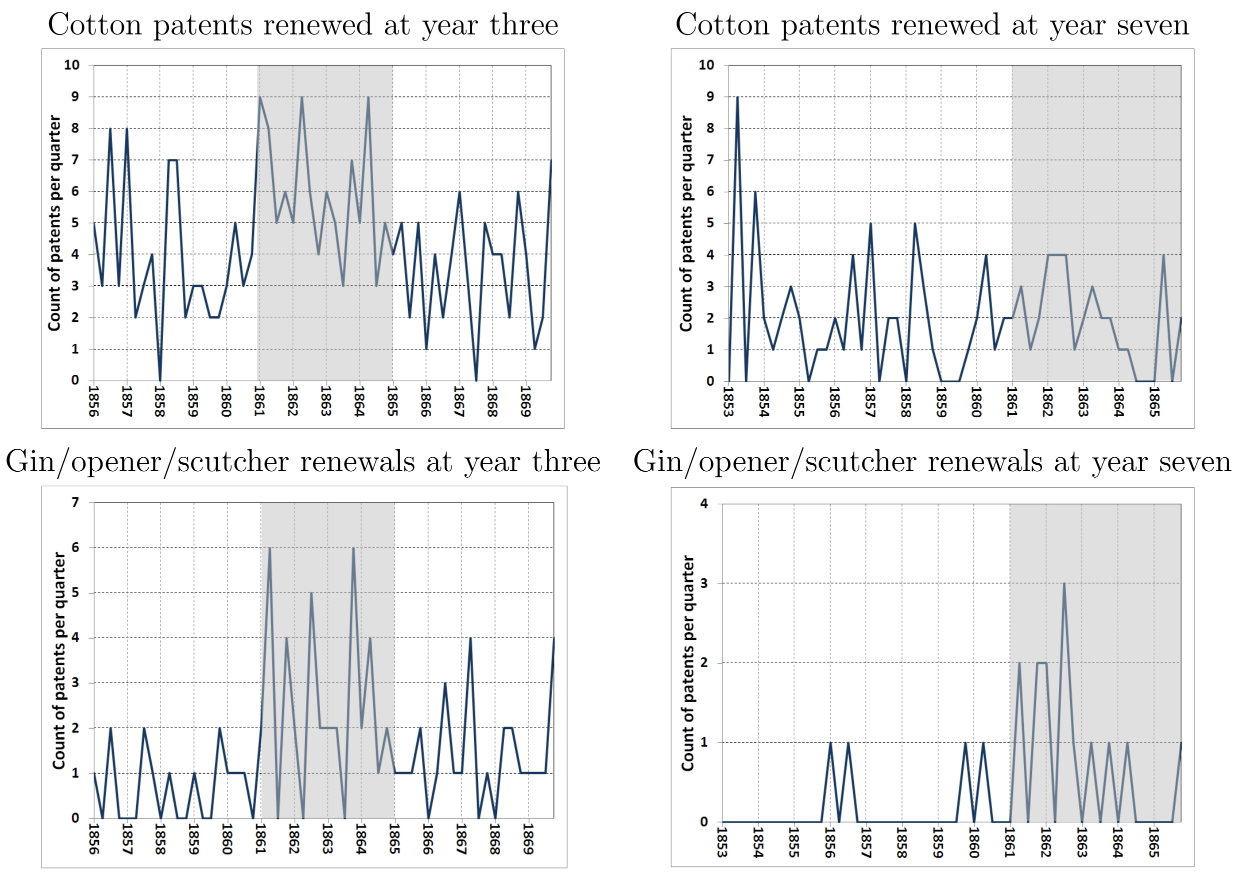
An important feature of these results is that there was a high level of patents filed in years 1862-1864 which were renewed after three years, and in some cases after seven years. For most of these, the renewal fees would have been paid after the end of the Civil War, during a period in which the markets were returning toward their pre-war equilibrium levels. This suggests that, had these patents been available prior to 1861, they likely would have been worth patenting given that the initial patenting fee was only one-half or one-quarter of the renewal fees. The point is that these technologies

[46]For example, an invention that fills a small technological niche may have long-term viability, but may not be broadly applicable and may also fail to arouse the interest of inventors. In contrast, an invention may be widely adopted upon introduction, but may also quickly become obsolete if further technological improvements are relatively straightforward. Finally, a novel but imperfect invention may arouse great interest among contemporary inventors and thereby generate follow-on innovations which soon render the original idea obsolete.

[47]For comparison, £100 in 1860 is equivalent to £7,020 2010 pounds using a retail price index deflator, or £65,2000 when deflating by average earnings (calculator available through the Measuring Worth project at www.measureingworth.com).

were most likely not available prior to 1861, which suggests that there was an increase in new and valuable innovation during the 1861-1865 period.

Figure 19: Cotton-related and gin/opener/scutcher technology patent renewals



"At year three" indicates patents for which the renewal fee was paid in to keep the patent in force beyond year three. "At year seven" indicates that the renewal fee was paid to keep the patent in force beyond year seven.

A.11.2 Valuing patents using foreign patent filings

This section uses patent data from India and the U.S. to assess whether the 1861-1865 period saw an increase in cotton and textile related patents which were widely applicable. This approach has been used previously by Lanjouw *et al.* (1998). The motivation behind this measure is that observing a British invention which was patented abroad indicates that the invention was viable in a wider range of circumstances. The U.S. and India are used both because data from these locations are available and because they represent significantly different environments in which the technologies must operate.[48] India was primarily a producer of low-quality raw cotton at this time. The U.S. was both a major producer of mostly high-quality cotton as well as an important cotton textile manufacturing center. However, patents filed during the Civil War were valid only in the North, which excluded all of the main cotton growing districts, but included most textile manufacturers.[49]

I begin by analyzing Indian patent data. These data, which I gathered from original printed records, cover 1859-1879. During this period, 1,138 Indian patents were granted, of which 429 went to inventors based in Britain. Each Indian patent was manually reviewed in order to identify textile and cotton related technologies.[50] Most of these patents are either for cotton gins, or for balers and packers, which were used to prepare the cotton for shipping. Table 14 describes how the share of patents made up of all cotton-related technologies, gins, and balers/packers, changed during the 1861-1865 period. The three left columns consider the share of these technologies in all Indian patents, while the right side looks at the share in only Indian patents by inventors based in Britain. There is evidence of a significant increase in the share of patents for gins and cotton-related technologies by British patent holders during the shock period. This is consistent with an increase in inventions in Britain which were also applicable in India.

Table 14: Share of Indian textile patents by British inventors

	Share of all Indian patents			**Share of patents by British inventors**		
	Cotton	Gins	Balers, packers	Cotton	Gins	Balers, packers
Shock Indicator	0.0442***	0.0249**	0.0167	0.126**	0.0720**	0.0482
(1861-1865)	(0.0145)	(0.00993)	(0.0117)	(0.0446)	(0.0295)	(0.0350)
Observations	23	23	23	23	23	23

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Annual data covering 1859-1879. All regressions include a constant.

The U.S. patent database covers 1857-1873 and includes 94,141 patents, of which

[48] The technologies used by U.S. textile manufacturers tended to differ somewhat from those used by British producers. A classic example is that the British generally used mules for spinning, which could spin finer thread counts and use lower quality cotton, but also required highly skilled operators, while U.S. manufacturers tended to use ring spinning technology that required higher quality cotton but could be operated by less skilled workers.

[49] There was a separate Confederate Patent Office operating in the South at this time, but given the uncertainty of the war and the difficulty of communication caused by the Union blockade, it was not successful at attracting patent filings by foreigners.

[50] Patents mentioning "cotton" in the title were coded as cotton patents, patents with "gin" in the title were coded as gins, etc.

1,160 were held by British inventors.[51] Using the inventor name and patent title I attempted to match each of these inventions to a patent filed in Britain, in order to identify a patent family. A total of 974 U.S. patents (84% of 1,160) were matched to British patents.

My interest is in whether there was an increase in cotton-textile-related patents in the U.S., by British inventors, corresponding to the increase observed in British patents.[52] Because there was a reduction in the fees paid by foreign patent holders in the U.S. in 1862, my analysis must focus on the share of textile and cotton-related patents in total U.S. patents by British inventors, rather than the raw number of patents. Table 15 presents results for textile-related technologies. These show evidence that there was an increase in the share of cotton-related technologies in U.S. patents by British inventors during the 1861-1865 period.

Table 15: Share of textile patents in total U.S. patents by British inventors

	Spinning	Weaving	Cotton	Wool	Linen	Silk
Shock	0.0317	-0.0313*	0.0338*	0.0191	-0.00484	0.00358
Indicator	(0.0357)	(0.0174)	(0.0176)	(0.0148)	(0.0191)	(0.00914)
Obs.	14	14	14	14	14	14

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Annual data covering 1857-1873. All regressions include a constant.

Table 16 applies the same exercise to spinning technology subcategories. There appears to have been an increase in the share of patents in the gins subcategory, as well as in bearings. Overall, this provides some evidence of an increase in British cotton-textile-related innovations flowing to the U.S. during the Civil War period.

Table 16: Spinning subcategory patents' share of total U.S. patents by British inventors

	Gins	Openers/ scutchers	Carding machines	Combing machines	Mules/ twiners	Rollers, etc.	Bearings	Finishing
Shock	0.0151***	0.00230	-0.000140	0.00690	-0.00525	-0.0171	0.0227***	-0.00813
Indicator	(0.00408)	(0.00460)	(0.00984)	(0.00497)	(0.00805)	(0.0169)	(0.00441)	(0.00792)
Obs.	14	14	14	14	14	14	14	14

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Annual data covering 1857-1873. All regressions include a constant.

[51] These data were generously shared by Tom Nicholas.

[52] For a comparison of the U.S. and British patent systems, see Khan (2005).

A.11.3 Valuing patents using contemporary publications

A contemporary periodical can be used to highlight the interest or excitement generated by a new patent upon its publication. This approach has previously been used to value historical British patents by Nuvolari & Tartari (2011). This section takes advantage of data that I collected from *Newton's London Journal*, a monthly publication devoted to covering new patents and other technology-related topics. This journal was published by William Newton & Sons, one of the preeminent patent agents in London. Among the *Journal's* stated goals was making more easily available the information contained in patent filings, and to this end, each issue included abstracts from a selection of recently sealed (i.e., granted) patents, some of which were accompanied by detailed drawings.[53] Though they provide little information about the criteria used to select these patents, presumably they included those patents which were deemed by the editors to be the most important inventions, or those which would be of greatest interest to the readers. Thus, inclusion of a patent abstract in the journal is treated as an indication of the initial novelty of each patent, based on the judgment of a knowledgeable contemporary opinion.

The *Journal* is available from January 1855 - February 1866, meaning that any patent applied for from 1855-1864 should have been a candidate for inclusion. Matching these patents to the primary patent database allows me to identify patents of textile and cotton related technologies. Because the total number of abstracts may have been limited by space constraints, the analysis focuses on the share of published abstracts made up of cotton-textile-related technologies. The analysis is based on the date the patent was filed, rather than the publication date, so for example, I look at all patents which were filed in 1861 and then subsequently published, and analyze the share composed of textile-related patents.

Table 17 presents results for the main textile technology categories and input types. These results show an increase in the share of abstracts for spinning and cotton-related technologies during the 1861-1865 period, as well as a smaller increase in patents related to wool. Table 18 shows similar results for spinning technology subcategories. The only significant result is an increase in the share of patents for gins during the 1861-1865 period. Together these results indicate that the 1861-1865 period was characterized by an increase in the number of cotton-textile-related patents, and particularly patents of cotton gins, which contemporary observers considered to be interesting or novel contributions.

[53]It is worth noting that patent abstracts were only included after the patent had been sealed, so publication was often as long as a year after the initial patent application was filed. This means that the editor would have had some perspective from which to judge the influence of a patent before including it in the journal.

Table 17: Share of published abstracts composed of textile-related patents

	Spinning	Weaving	Cotton	Wool	Linen	Silk
Shock	0.0501***	-0.00765	0.0307***	0.0206***	0.00795	-0.00187
Indicator	(0.0112)	(0.0133)	(0.00732)	(0.00337)	(0.00654)	(0.00565)
Obs.	10	10	10	10	10	10

Standard errors in parentheses. Annual data covering patents from 1855-1864.
*** p<0.01, ** p<0.05, * p<0.1.

Table 18: Share of published abstracts composed of patents in spinning subcategories

	Gins	Openers/ scutchers	Carding machines	Combing machines	Mules/ twiners	Rollers, etc.	Bearings	Finishing
Shock	0.00866**	0.00339	0.00772	0.000586	0.00330	0.00304	0.00546	-0.00188
Indicator	(0.00288)	(0.00287)	(0.00591)	(0.00331)	(0.00422)	(0.00224)	(0.00340)	(0.00415)
Obs.	10	10	10	10	10	10	10	10

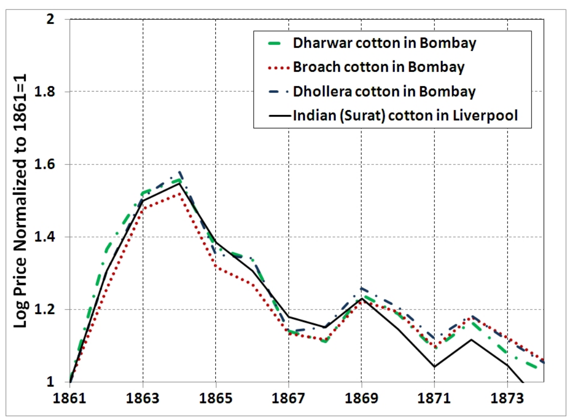
Standard errors in parentheses. Annual data covering patents from 1855-1864.
*** p<0.01, ** p<0.05, * p<0.1.

To summarize the results of this section, it appears that there was a significant increase in British patents of high-quality cotton textile technologies, and particularly early stage technologies such as gins and openers/scutchers, during the U.S. Civil War. This holds whether patent quality means long-term viability, as measured by payment of renewal fees, wider applicability, as measured by patents outside of Britain, or initial novelty, as measured by being mentioned in a contemporary periodical.

A.12 Comparison of Bombay and London prices of Indian cotton

In this appendix, I look directly at cotton prices in Bombay in order to check if there appeared to be an increase in the gap between the Bombay and London prices of Indian cotton which would suggest that the prices were being influenced by quality improvements. While there is not a wealth of price data available, Atkinson (1897) does provide price indexes for three varieties of Indian cotton on the Bombay market. Figure 20 graphs these Bombay market prices together with the Liverpool market price, where all prices are presented in logs and normalized so that 1861=1. This is done to eliminate the need to compare in level terms, which is difficult given exchange rate fluctuations. We can see that these prices are moving together, which suggests that there were no quality improvements in the benchmark cotton varieties between the Bombay and London markets that could be affecting the price data used in Section 6.

Figure 20: Comparison of cotton prices on the Bombay and Liverpool markets



Liverpool price data gathered from *The Economist* magazine. Bombay price indices were constructed by Atkinson (1897).